

# IA of AI

Convey UX 2017



# Agenda

Introduction

What is Artificial Intelligence (AI)

Where do information architecture (IA), user experience (UX) and content strategy (CS) fit in

How do we get involved

Why should we care



# INTRODUCTION



# Me

Serial Career Changer

Transitioned to Technology 1995

Became Information Architect 1998

Microsoft 1999 – 2006

Discovered Information Retrieval 2003

Ascentium Digital Agency 2006 – 2010

Daedalus Information Systems 2010 – 2012

Portent Interactive January 2012 – 2 015

Brightedge 2016 -



Me

Them

Shared Vision for workshop

## Information Behavior Bates (1980)

A typical search evolves as information is gathered in bits and pieces along the way

Process involves:

- Searching many different places/sources
- Using/changing search technique for different places
- Changing search goal as learn along the way



(1989)

Marcia Bates is an information scientist at UCLA. Her model tells us that the user starts out with a query and traverse to a point where they find something of interest. Their query is reformulated with this new information and continues in a changed state until the next piece of information affects a change which... well, you get the idea. We used to call this "browsing."

"An important thing we learned early on is that successful searching requires what I called "berrypicking." It is usually a fallacy to think that everything you want is going to be found in one place. Good searchers "berry pick," that is, they search for a topic in numerous places, just as you would go around in the woods picking blueberries or huckleberries. (I drew this example from actually searching for berries in the woods in the Northwest, when I lived in Seattle.)

Berrypicking involves 1) searching many different places/sources, 2) using different search techniques in different places, and 3) changing your search goal as you go along and learn things along the way. (See Bates, Marcia J. "The Design of Browsing and Berrypicking Techniques for the Online Search Interface." *Online Review* 13 (October 1989): 407-424.)

This may seem fairly obvious when stated this way, but, in fact, many searchers erroneously think they will find everything they want in just one place, and second, many information systems have been designed to permit only one kind of searching, and inhibit the searcher from using the more effective berrypicking technique. For example, in a technical report database, you might be able to search by word but not browse by the name of the laboratory that produced the report."

<https://www.quora.com/profile/Marcia-J-Bates/Online-Search-and-Berrypicking/An-important-thing-we-learned-early-on-is-that-successful-searching-requires-what-I-called-berrypicking-it-is-usu-1>

## Information Behavior Jansen (2000)

Users make 2.84 queries using an average of 2.35 terms

1<sup>st</sup> query is unique, others are modifiers of this

Decline in length of queries

Users viewing fewer documents

Spend less time evaluating documents



Possible reasons for shorter queries:

- Higher precision in search results

- Users more sophisticated about information needs

- Users forming better queries

We're in the web world albeit new:

- Free text rules

- Advanced search scares people

Begin the decay of discernment: ease of search, plentitude of results without effort,

PageRank novelty

# Information Behavior Mai (2016)

Quality of Information

Part of a spectrum

Data >> Information >> Knowledge

Quality depends on individual characteristics

- Contextual
- Situational
- Environmental
- Emotional



Jens Erik Mai, 2011

# WHAT IS ARTIFICIAL INTELLIGENCE



# AI Manifestation 1

www.bing.com/search?q=%3Bomledom%2Fcp%2C&form=UWDFDF&pc=UWDFD

Hands in wrong position on keyboard

omledom/cp,

Web Images Videos Maps News

Also try: [LinkedIn Tutorial PDF](#) · [Already on LinkedIn Sign in](#) · [LinkedIn Sign in](#)

581,000 RESULTS Any time ▾

**Sign Up | LinkedIn**  
<https://www.linkedin.com/myGroups> ▾  
LinkedIn Make the most of your professional life. Join LinkedIn. First name. Last name. Email. Password (6 or more characters) By clicking Join now, you agree to the ...

**Chas L. Perry II- Mastery of Self is Mastery over All Else ...**  
<https://www.linkedin.com/in/chasperry2thewisevisionary7>  
Business Development-Inside Sales, ... · Information Technology and Services · 500+ connections  
View **Chas L. Perry II- Mastery of Self is Mastery over All Else's** professional profile on **LinkedIn**.  
LinkedIn is the world's largest business network, helping ...

[olavsolberg.no](http://olavsolberg.no)  
[olavsolberg.no/wp-admin/network/omledom-cp](http://olavsolberg.no/wp-admin/network/omledom-cp) · [Translate this page](#)  
We would like to show you a description here but the site won't allow us.

What I was searching for



# An Algorithm is...

Set of instructions (procedure or function) that is used to accomplish a certain task

“A computable set of steps to achieve a desired result. “ National Institute of Standards and Technology

“Math that computers use to decide stuff.” Kevin Slavin



algorithms = math that computers use to decide stuff

Algorithm is a recipe for performing a certain task. A data structure is a way of arranging values (array, tree, graph, list, etc.)

hash table: hash marks on twitter but computer numbers, quick way to store and retrieve values/items

arrays: chunk of contiguous memory a program can access b using indices >> one index per dimension >> arrangement of “boxes” where program stores values

Algorithms lock into behavior with no human supervision

Designed for a machine dialect: happens all the time on Google, adjust one thing - something else happens = unintended consequences

# Algorithms

Algorithms process instructions according to formulas and rules that produce desired results if followed.



Roger Martin, Rotman School of Management, University of Toronto  
<http://rogerlmartin.com/>

## 3 Features of Any Algorithm

Correctness

Maintainability

Efficiency



Correctness: Does it produce the right answer

Maintainability: can be kept operational

Efficiency: uses resources wisely, e.g. binary tree there are only 2 options

# Algorithms work on Data Structures

Stack  
Queue  
Bucket Sort  
Linear Search  
Binary Search  
Interpolation Search  
Hash Table  
Trees  
Tries



**Stack:** LIFO (last in first out) data structure with prescribed order for additions and deletions

**Queue:** FIFO (first in first out) data structure used mostly for additions

**Bucket Sort:** Algorithm divides items into bins/buckets then sorts buckets and concatenates the bucket content for sorted results

**Linear Search:** examines every item in array until it finds a match

**Binary Search:** algorithm calculates index halfway between minimum and maximum and divides, searches the array for the target, keeps dividing and searching until it finds the right value

**Interpolation Search:** uses the value of the target item to guess which array has the value

**Hash Table:** maps data to location in data table and assigns unique value – hashing function to map keys to the location, collision resolution policy for when keys collide (2 keys that hash the same value)

**Trees:** ordered (matters) and unordered (doesn't matter) = goal is traverse all nodes (leaves on the tree) in some order and perform the operation. Traversal types: pre order (node then children), in order (left child, node, right child), post order (left child, right child, node) depth first (all nodes left then all nodes right). Sorted trees: nodes arranged so that an in order traversal process them in sorted order.

**Tries:** tree that holds strings. Each internal node represents a single letter – leaf nodes can represent more than one letter, B-Trees are used to store large records, organized by key value – position in the tree defines the key value (not the reverse) – children of node share string prefix of parent leaf

# Significant Algorithms

**Search engine indexing**

**PageRank**

**Public Key Cryptography**

Error Correcting Codes

**Pattern Recognition**

Data Compression

Databases

Digital Signatures

*“At the heart of every algorithm in the book is an ingenious trick that makes the whole thing work.”*



From: 9 Algorithms that Changed the Future – John MacCormick

What makes a great algorithm?

- Used by computers every day
- Address concrete, real-world problems
- Relate primarily to the THEORY of computer science [efficiency with which problems can be solved with a model of computation supported through algorithms]

# Search Engine Indexing

Internal &  
External  
Algorithms



1. Crawl
2. Convert
3. Label
4. Store
5. Retrieve



# PageRank (1999)

PageRank is a pre-query valuation

Uses the links pointing to document

Intelligent Surfer

Has no relationship to the subject of the query

Subject to external manipulation

## The PageRank Algorithm

$$PR(A) = (1-d) + d \left( \frac{PR(T1)}{C(T1)} + \dots + \frac{PR(Tn)}{C(Tn)} \right)$$

Where

- PR(A) is the PageRank of Page A
- PR(T1) is the PageRank of page T1
- C(T1) is the number of outgoing links from the page T1
- d is a damping factor in the range of  $0 < d < 1$ , usually set to 0.85

Source: Google Hacks, p. 295



Based on academic citation model

1998 named one of the top 100 Websites by PC Magazine “uncanny knack for returning extremely relevant results”

Ranking based on number of links to the page

Used link structure of Web to build a Markov Chain with a primitive transition probability

Intelligent Surfer: algorithm picks a link to exit page – one that is topically related to the query

First introduction of “loose authority” determined by adding up the “authority” scores of the pages linking in

Discounted pages linking to each other (black hat link ring)

Complications:

Assumes link vote of authority, does not consider commercial value of links

Ability to link limited to subset of users

Orphan pages

Users no longer “surf” randomly

Does not scale

## PR Based & the Random Surfer

Intended to avoid spider traps

Imagine a random Web surfer

At any time  $t$ , surfer is on some page  $P$

At time  $t+1$ , the surfer follows an outlink from uniformly at random

Ends up on some page  $Q$  (from page  $P$ )

Process repeats indefinitely

Let  $p(t)$  be the vector whose  $i^{\text{th}}$  component is the probability that surfer is at page  $i$  at time  $t$   
 $p(t)$  is a probability distribution on pages



Slide courtesy of Dr Jun Wang, University College London, BCS Search Solutions IR Tutorial November 2011

Random Surfer (spider follows “randomly selected links) examines all of the links and follows one to destination, does that at destination

- Random Surfer authority score: % of time random surfer would spend visiting the page (added to the hyperlink score)
- Restart probability = 15%, surfer does not select a link and instead “jumps” to another page

Since updated to the “reasonable surfer” to reflect choice that is semantically related to original request

# Public Key Cryptology

Enables exchange of confidential information between online entities

128 bit encryption = length of shared secret key

Encryption relies on 1 way action – something that can be done and not undone

On <https://> sites, client and server exchange public/private keys



Uses sequence of algorithms to generate number sequences that are hard to predict

2 large prime numbers for security – prime # is one that is greater than 0, only factors are 1 and itself, composite number is counting number greater than 0 that is not a prime number

Public # (known to both)

Private # (known to each)

Encrypted # is the combination of all of both public and private = shared secret

Diffie Hellman Key algorithm 1976

RSA famous public key encryption system

Discrete exponentiation – combining of encryption keys

Discrete Logarithm – deconstruction of encrypted message

# Pattern Recognition

Ability for computer to act intelligently based on input data with a lot of variability

- Decision Trees
- Nearest neighbor classification
- Neural Networks

Classification

Ideal replaced by practical

Constant decision what problem to work on

- Value based

Pandemonium



Decision trees: run through series of questions where answer determines outcome

Nearest neighbor: find in training data and use most similar to predict the unsorted data

Neural networks: based on biochemistry, electric and chemical signals

- some connections dedicated to send, others to receive
- neurons are either idle or firing
- stretch of incoming signals determines the neuron firing
- 2 types of inputs: excitatory (adds up to total) and inhibitory (subtracted from total)
- each neuron assigned a threshold
- signal here is data related to a pre-assigned condition

Explicit teaching based on user data

Learning from example based extracted characteristics from training set of documents

### 3 Information Retrieval Models

Boolean Model: framework of document sets and standard set of operations on sets

Vector Model: framework composed of t-dimensional vector space representing queries and documents as vectors

Probabilistic Model: framework based on probability distributions of terms on documents and queries (Bayes theorem)



These are for unstructured text

# Boolean Model

Framework: considers query terms as either present in or absent from collection

Term frequencies in document seen as binary

Query is a set of terms linked by operators: AND, OR, NOT

Predicts every document is either relevant or not relevant

Weights assigned to terms to compute rank

Term-term correlation to establish relationship between terms

Document diversity addressed by:

- TF/IDF weight
- Document length normalization



Assigning weights to terms allows computing a numeric rank to each document with regard to query

Term term correlation establishes a relationship between any two terms based on their joint co-occurrence inside documents of the collection (phrase searching)

Term frequency weights: value or weight of term simply proportional to frequency in document

Exhaustivity: property of document descriptions – exhaustivity of document description quantified as number of index terms contained

Specificity: property of index terms – specificity of a term can be quantified as inverse function of the number of documents in which it occurs

Zipf's Law: power law equation

TF/IDF: document normalization divides document rank by length so that longer docs are not at an advantage strictly by size (makes frequency of term more meaningful)

Normalized by size in bytes, number of words or vector norms  
very important ranking principle

# Vector Space Model

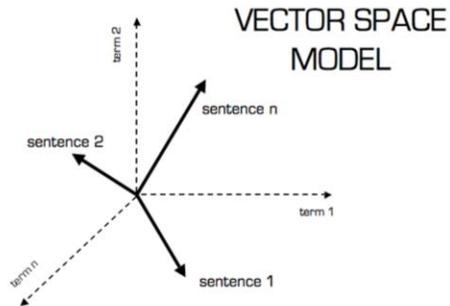
Compensates for Boolean limitations by opening possibility of partial matching

- Assigns non-binary weights

Framework: T-dimensional vectors for documents and queries

- Standard linear algebraic operations

Sorts (ranks) documents in descending order of similarity  
Consider documents that partially match



## Advantages

- Term weighting scheme
- Partial match strategy
- Rank by degree of similarity
- Natural document length normalization

## Disadvantages

Index terms presumed to be semantically independent

# Probabilistic Model

Framework: Probability distribution of terms on documents and queries

- Utilizes Bayes Theorem
- Assumes set of exactly relevant document

Query specifies properties of the ideal answer

Assigns measures of similarity

Assumes mutually independent terms

User interaction through feedback loop to make ideal answer more accurate



Query is a subset of index terms, document is represented by a vector of binary weight indicating the presence or absence of index terms

## **Advantages**

Optimality as documents are ranked in decreasing order of probability

## **Disadvantages**

- Ideal often not realized because user relevance often relies on non-document factors
- Need to guess the initial similarity of documents
- Term frequency within document not considered
- No document length normalization

# ORIGINS OF AI



# Two Schools of AI

Symbol Processing

Neural nets



# Symbolic AI

Intelligence = symbol manipulation

Fixed and formal rules

Assume: all intelligent processes are forms of information processing

Computer processes symbolic representations (1s/0s) according to formal rules (program)

Plato's rationalism

GOFAI



Intelligent processes = perceiving, reasoning, calculating, language use

Language is symbolic: eg a dog does not look like the word that represents it  
3 characteristics of Plato's rationalism: Psychological assumption that human intelligence is symbol-manipulation according to formal rules, Epistemological assumption that knowledge is formalized and can be expressed in a context-independent, formal rules or definitions, Ontological that reality has a formalized structure built on objective, determinant elements each of which exists independent of the other .

Dreyfus added the Biological assumption, rules and symbols implemented by the human brain in the same way as by a machine

GOFAI = good old fashioned AI – meat and potatoes AI – train the computer without the need for understanding

# Artificial Neural Networks

## Connectionism

Neural networks made up of input layer, interstitial layers and output layer

Good at: pattern recognition, categorization, and behavior coordination

Knowledge comes from the connections not symbol interpretation

Past experience used to form intelligence in current state

Heideggerian AI (HCI component needed)



Re-emerged in 1980's

Layers of data – decisions inform up the line (backpropagation)

Autonomy: without human supervision

Automate: replace human effort

Intelligent processing modeled on structure and operation of human brain instead of digital computer – neurons and synapses, receptors and reactors

Neurons as processors with input/output functions

Intelligence is a product of the neuron connections

The ANNs of the 1980s could never conceive of the vast amount of personal and behavioral data used in today's neural networks (deep mind, Watson). Examples: IoT (intelligent machines), Watson (expert systems)

Cannot generalize as humans do, cannot perform functions that require "common sense" (must be programmed)

Heideggerian AI: intelligence is situated in the world and does not require rules.

Terry Winograd (Stanford): design of computers must include consideration that computers must function in a human world and communicate with human users and not impose their own rationalistic logic on surroundings.

# Turing (1948)

## Imitation Game

### Objections to machine intelligence

- Theological
- Head in Sand
- Mathematical/philosophical
- Consciousness
- Lady Lovelace

Reward Signal increases probability of repetition events leading to it

Suitable imperative: one that regulates the order in which the rules of the logical system are applied

Program the learning



Computing Machinery and Intelligence: A.M. Turing; Mind: Quarterly Review of Psychology and Philosophy ; October 1950

Imitation Game: 3 individuals, man, woman and interrogator (apart from the other two). Object of game is for interrogator to decide which of the other two is a man or a woman based on answers. Substitute machine for one of the individuals, can interrogator determine machine from person based on answers  
AI for Turing is a digital machine able to play the Imitation Game

Some objections addressed by Turing;

Theological: machines have no soul and neither do high-level animals

Head in Sand Objection: too scary to accept

Mathematical Objection: Godel's theorem on limitations of discrete state machines (there are questions that cannot be answered, certain things a machine will never be able to do) - all humans are also incapable of answering some questions

Consciousness Argument: dismissed as solipsistic (solipsism holds that knowledge of anything outside one's own mind is unsure)

Lady Lovelace Objection: machines cannot originate anything – humans take risks, machines cannot

# Pandemonium (1959)

Oliver Selfridge

Initially intended as a model of letter perception

Decision making entity involving 4 “demons”

4 distinct layers: storage >> filter and pass >>  
cognitive >> decision-making layer

Top Layer decides what information has been  
presented to the system (discernment)

Requirements:

- Well defined problem
- Unbiased decision making
- Single tamper-proof labeling of behavior

Feed-forward and feedback connections between  
layers



Wikipedia calls him the “Father of Machine Perception” – related to Selfridges stores in England

Supervisor of Minsky at MIT

Associated with neural networks and pattern recognition

Intellectual processes can be carried out by hierarchy of simultaneously functioning submachines (demons)

Cognitive demons and data demons use abstracted data for evidence of specific propositions. Demons record events and recognize patterns

Demons = entities that perform intellection processes that can be carried out by a hierarchy of simultaneously functioning submachines.

Demons receive input through continuous interaction that leads to conclusion on what the input “is”

Layers group demons by specific task

- Bottom: collect and stores information
- 3<sup>rd</sup> Layer: selects and passes along good candidates
- 2<sup>nd</sup> layer: filters and weighs >> “shrieks” information up to top layer where decision is made
- Top layer: biased towards loudest shrieks and draws own conclusion regarding the output

Used human behavioral psychology for models

Hierarchical letter identification: visual features are mapped onto abstract letter identities through a series of increasing invariant representations

Layers of feature and letter detectors – building blocks of inputs and outputs

Template matching model

Unbiased decision making: encourage random behavior for a wide-range of decision-making behavior

“The visual world can be described in terms of variations in special frequency, that changes in luminance across space...The key to both approaches [measures of identification thresholds and measures of variations in identification thresholds a function of the characteristics] involves comparison of human performance with that of an ideal observer.” Perception: From Pixels to Pandemonium: Jonathan Granger, Arnaud Rey, Stephane Dafau August 2008

# Pandemonium (1959)

Developed by Oliver Selfridge and Frank Rosenblatt

Selfridge Rosenblatt character (letter)  
recognition based on component features



# Perceptron (1957)

Developed by Frank Rosenblatt, psychologist at Cornell  
Artificial neural networks (ANN) = many interconnected processing units for parallel processing

Trained not programmed

1. Input addition
2. Comparison with threshold value
3. If threshold met or surpassed, output activation

Modifiable connections adjusted according to “learning” algorithm

Perceptrons are not without limitations



Signal transmission network consisting of sensory units, association units and response units

Types: single layer, multilayer, cross coupled, multilayer back couples

Backpropagation algorithm (Rumelhard 1986) adaptively corrects weights based on adjusted pattern classification from training set.

Birth of Symbolic AI

Single layer: one way, no hidden components limited pattern recognition capacity

Multilayer: feed forward with multiple hidden elements

Cross coupled; connections made to join units of the same type

Multilayered back coupled: feedback paths from elements further back in the process (near the output) – possesses a universal approximation property

Error correction learning algorithm

- Binary outputs
- Feed forward

Limitations

- Theoretical learning curves for error correction procedure
- Determination probability that solution exists
- Representation of complex environments
- Efficient reinforcement
- Recognition of abstract concepts

Debunked by Marvin Minsky and Samuel Papert in 1960's – they favored the Symbolic AI model developed in 1956)

Symbolic AI: capabilities of computer to manipulate symbolic representations in a ways sensitive to logico-syntactical (discrete) structure

Manipulated and transformed according to rules and strategies (logical, programmed and rationalistic

Neural Networks seen as self-organizing based on training

Cannot process anomalous problems (those resistant to an acceptable solution)

## Pandemonium Layers

Bottom layer: store data

3<sup>rd</sup> Layer: select, weigh, filter and pass along data

2<sup>nd</sup> Layer: “cognitive demons” decide which information from 3<sup>rd</sup> layer process

Decision layer: single decision demon on what information is presented to the system for processing



Identified behaviors for Pandemonium

- Ability to define problem
- Unbiased decision making
- Single tamper=proof way of labeling “demon” behavior

# Marvin Minsky (1960)

Cognitive computer scientist

Co-founder MIT AI Laboratory

Symbolic AI

With Seymour Papert brought forth a 20 year “AI winter” with criticism of early AI Artificial Neural Network (ANN) approach



1927 – 2016

A humanist computer scientist

Symbolic AI = rule based system of symbol processing and manipulation based on selected training. Uses a representational structure, applies rules - trained

Neural Net AI = interconnected processing units producing cycles of input feeding and weight adjustment. 3 part processing operation: input addition, comparison with threshold value, output firing

# ELIZA (1963)

Human mediated

Early computer/human conversation (NLP)

Heuristic programming

- Keyword identified (input)
- Sentence transformed according to rule associated with identified keyword
- Choose appropriate transformation – if none available, choose most likely/earlier transformation
- Generate responses.

Keyword dictionary contains composition, assembly and decomposition rules



Recognition of semantic patterns in text  
NLP = natural language processing

Name chosen because of incremental learning by “teacher” example – e.g. Eliza Doolittle in My Fair Lady

Input sentences analyzed on basis of composition rules triggered by keywords that appear in input text. Responses generated by assembly rules associated with decomposition rules (a data structure that searches text for specific patterns and then decomposes text into disjointed constituents) and reassembly rules (specification for construction of new text by means of recombination of old and possible (new) constituents).

No understanding

There are elements in human conversation that do not take place in text, available only to humans in F2F meeting

## Eliza Global Context

Global Context is key to understanding

Sub-contexts emerge as conversation continues  
for consequential richness

Individual participants bring Belief Structure

ELIZA scripts (previous learnings) establish a  
global context for future “understandings”

Broad context framework only



Global context assigns meaning to what is being said in most general way.

Belief Structure: emerges from individual's intellectual life (highly logically organized) and life experiences

Broad contextual understanding due to general nature of scripts development

## Dreyfus (1964)

Rationalist assumption of “ordered reality” is flawed

Knowledgeable reality itself lacks rational structure

Inter-relatedness between humans and the world

Human world filled with experience structures-  
neither subjective or objective

Intelligence is discovering meaningful structures and  
applying meaningful behaviors independent of fixed  
rules



Hubert Dreyfus (AI critic) computer scientist at MIT teaching philosophical theories of knowledge and perception

Recruited by RAND Corp in 1960's as a philosophical consultation to their AI program  
Published highly critical article on AI “Alchemy and Artificial Intelligence” and “What Computers Can't Do” 1972, republished in 1992 and “Mind over Machine” 1986

Principle focus is unique and intuitive way humans experience the world and develop manners of getting around in it

Intelligence is situated – co-determined by situation/environment

Experience structures = smells, feelings, threats, obstacles, goals

Humans experience the world as a single whole before its individual components  
Sensorimotor intelligence: human skill used in perceiving, recognizing, moving and manipulating objects as well as coordinating and integrating perception and movement (localized complex feedback system of nervous system, senses, glands and muscles)

# Perceptrons & AI Winter

W I N T E R   I S   C O M I N G



# Norvig & Russell (2004)

## Artificial Intelligence: A Modern approach

### Types

- Systems that think like humans (neural)
- Systems that act like humans (Turing)
- System that think rationally (logic solvers)
- Systems that act rationally (perception, NLP, Planning, Navigation)



# Embodied Agents

Internet of Things

Goal driven planning

Reactive agents

Search, planning and logic (robotics)



Roomba  
GPS

## Minsky on Creativity

“There’s no such thing as “creativity” in the first place. I don’t believe there’s any substantial difference between ordinary thought and creative thought...I’ll argue that this is really not a matter of what’s in the mind of the artist – but what’s in the mind of the critic...”



### Minsky: Why People Think Computers Cannot

He goes on to elaborate that some humans are better at learning than others and this accounts for creativity

Creativity could be just the consequence of childhood accidents in which a person’s learning is more self-applied than others.

If machines are made to learn better they can be creative

Would require computers to be programmed for abstract thinking in addition to logical reasoning

# Minsky on What AI Best Suited To

Search

Learning Systems

Pattern Recognition

Planning

Induction



Minsky

Search: search engines

Learning Systems:

Pattern Recognition: fraud detection

Planning: GPS

Induction: IBM Watson

# Search

Requires additional structure

Near to/close to

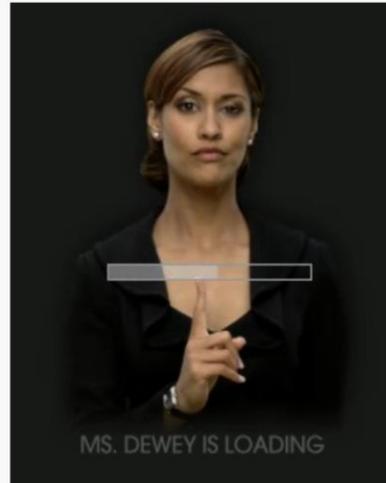
Solve for one, solve for many

Personalization



## AI and Search: Mrs. Dewey

Librarian with an attitude  
Product of Microsoft Live Search  
Processing results slow  
No user influence opportunities  
Novelty act?



# AI and Search: Wolfram

- Developed Mathematica software
- Powers iPhone 4 Siri
- Searching own “knowledge base” (limited corpus)
- Not for every type of search



Knowledge base is not an index – not crawled and refreshed with new data from outside resources

# Learning Systems

Use past behavior to predict future action using human planned heuristic methods

Reinforced learning model that leads to a secondary reinforcement model that is more autonomous

- Reinforcement is reward
- Extinction is unlearning

Grade on curve of computer's acquired capability



Generalized past experiences

Success is reinforced decision models

- Can have secondary reinforcement models (more autonomous)

Reward for partial goals (local reinforcements)

Grade on curve of computers acquired capacity

Reinforcement = reward

Unlearning = extinction

# Pattern Recognition

Ability for computer to act intelligently based on input data with a lot of variability

- Decision Trees
- Nearest neighbor classification
- Neural Networks

Classification

Ideal replaced by practical

Constant decision what problem to work on

- Value based

Pandemonium



Decision trees: run through series of questions where answer determines outcome  
Nearest neighbor: find in training data and use most similar to predict the unsorted data

Neural networks: based on biochemistry, electric and chemical signals

- some connections dedicated to send, others to receive
- neurons are either idle or firing
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- 2 types of inputs: excitatory (adds up to total) and inhibitory (subtracted from total)
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- signal here is data related to a pre-assigned condition

Explicit teaching based on user data

Learning from example based extracted characteristics from training set of documents

# Planning & Problem-Solving

Large assembly of interrelated sub-problems

Choose appropriate sub-problems for solving selected problem

Logic Theory: prove theorem using heuristics:

- Similarity test
- Simplicity test
- Strong non-provability test

Heuristic programming



AKA Goal Seeking or Problem Solving

Intelligent systems that decide for themselves

Action and resource management

Given description of start state, a goal state and a sequence of actions. Outcome is to find the most efficient set of actions to achieve the goal

Transportation, scheduling

Interactive decision making: military planning,

# Heuristic Programming

Early training for AI

Self-learning

- substitutes machine learning for logic algorithms
- Ranks alternative in a branching decision tree

Achieves an approximate of the exact solution

ELIZA



Heuristics here mean common sense rules from experience (in this case, the programmer) , likely using vast personal data trove to build these use cases  
Counter part is Algorithmic programming that uses mathematically proven features, quantifying, logic driven

# AI and Induction



## IBM Watson

### Question answering machine

Performance: speed, confidence, estimation, clue selection, betting strategy

- Massive parallelism
- Pervasive confidence estimation
- Integrated shallow and deep knowledge

### Lexical Answer type



## Deep QA Project at IBM

Precursor Deep Blue, chess database that beat Gary Kasparov

3 years in development

Stores millions and millions of documents on room full of servers

Lexical answer type: word or noun phrase in the question that specifies the type of answer without deconstructing the question semantics

### Processing

- Parsing
- Classification
- Decomposition
- Automate answer source
- Evaluation
- Confidence estimation

Critical thinking vs. computational math

Computes and chooses between possible answers (module 5 will look at text classification and training more closely)

Wolfram's comment from NYT article: can only answer "factual" questions (db questions), cannot for an answer that has judgment

Discussion Question

# WHAT IS INTELLIGENCE?



# Machine Learning

Derives rules from a data set

A programming approach to problem-solving –  
composite of not a single algorithm

Model of real world using mathematic structure  
with decision-making rules

Objective function = desired outcome

Training set with adjusted parameters until goal  
achieved

Test set used to validate accuracy and effectiveness



# Probabilistic Machine Learning

Probabilistic framework can represent and manipulate uncertainty

Requires high capacity for flexibility to allow data to “speak for itself”

Universal inference engine using Monte Carlo



Infers plausibility models to explore observed data

Inference prediction for forecasting using Cox Axiom (spectrum: impossible to absolutely certain)

Dutch Book theorem used for degrees of uncertainty

Universal inference engine infers imputes that match a certain output

# Supervised Learning

Uses document-class pairs to indicate proper classes for given documents

Used human specialists for classification of “training set” used to “teach” system

- Assigns classes to documents
- Reviews machine classification performance

## 6 Algorithm types

- Decision Trees
- Nearest neighbor
- Relevance Feedback
- Naïve Bayes
- Support Vector Machine
- Ensemble



Labeled data

Regression (estimating relationships between variables for prediction)

Classification

Ranking

Nearest Neighbor (aka k-NN): no established classification model, done on the fly, classification decision based on nearest neighbor in predefined metric space, more focused on document features and less on global values application (bottom up, document based, classification)

Relevance Feedback (Rocchio): vector space model that allows modification based on user feedback (training set is the feedback mechanism)

Ensemble: Combines the output of independent classifiers, accuracy = better than random guessing. Meta classifier takes various classifiers prediction output for document and combines into a single prediction

# Unsupervised Learning

Unlabeled data

Clustering

Segmentation

Association

Algorithms

- Neural networks
- Independent component analysis



Neural Network: approximates human brain neural network of nodes and electrons

- Composed of 3 layers: query terms, document terms, actual documents
- Query terms nodes initiates inference process with sent signals to document term nodes
- Uses BM25 Probabilistic models that use term weighting (inverse document frequency, term frequency and document length normalization)

Independent component analysis:

Wikipedia: (ICA) is a computational method for separating a multivariate signal into additive subcomponents supposing the mutual statistical independence of the non-Gaussian source signals

# Reinforcement Learning

Evaluative feedback (user data)

- Sampled
- Evaluative
- Sequential

Rewards (expected for every possible future state)

Control

Optimal decisions as baseline

Bandit algorithms

Temporal Difference Learning



Inspired by human decision making

Evaluative feedback is based on decision effectiveness and appropriateness of available alternatives

Control: moving through all possible combination of environments/states with a sequence of actions that maximizes potential for reward

Bandit algorithms: based on slot machine “one armed bandit.” Algorithm must decide which decision to make in what sequence to maximize rewards

Collect a large, static, set of bandit decisions using real problems with a random selection algorithm

Supervised learning is a contextual bandit set of algorithms

Uses Stochastic gradient Descent (SGD) This consists of showing the input vector for a few examples, computing the outputs and the errors, computing the average gradient for those examples, and adjusting the weights accordingly.

Temporal difference learning: makes predictions about long-term implications. Errors are used as learning signals and later incorporates into a generalized learning objective [Google likely uses temporal difference learning for geo-based local profiles to inform decisions.] – modeled on human brain neuron firing of dopamine signals

# Deep Learning

“Deep learning, a form of machine learning based on layered representations of variables referred to neural networks, has made speech-understanding practical on our phones and in our kitchens, and its algorithms can be applied widely to an array of applications that rely on pattern recognition”

Stanford 100 AI Study



# Deep Brain (Google)

Jeff Dean (Google since 1999)

Goal is to go from learning bunch of steps to the ability to know what the next step is

Neural networks that learn complicated functions from data

Methods:

- Supervised (labeled examples)
- Unsupervised (patterns and data clustering)
- Reinforcement (right/wrong feedback)
- Deep Learning (collection of trainable math units which collaborate to compute complicated functions)



Google acquired machine learning companies over the last years: Deep Mind 2013  
Cannot write algorithms for all of the tasks, must write algorithms that learn from each other

Data Set

- Text (trillions of words in all languages)
- Visual (billions of images)
- Audio (thousands of hours of speech)
- User activity (searches, clicks, time on site)
- Knowledge Graph (billions of labeled relationships)

# Deep Learning

HUGE raw data training set

Results get better with more data, new/better algorithms based on observation and insight

Powerful processing hardware is key

Machine Learning requirements

- Ease of expression for many types of ideas/algos
- Scalable
- Portable
- Reproducible
- Extensible

RankBrain search engine relevance model



Text (documents, queries)

Visual data (images)

Audio (speech, music, sounds)

User activity (mark spam, engagement metrics, etc)

Knowledge Graph (acquisition of structured repository Freebase)

Hardware: Tensor CPU

Portable: use across many platforms

Reproducible: by others

Extensible beyond research phase

Uses: search, robotics, self-driving cars, healthcare, video retrieval, voice search, personal assistance (chat bots)

# Thought Vectors

Gregory Hinton – Google Research Fellow

Software learns to recognize patterns in digital representations

Virtual neural network

2006 Hinton's discovery of layering instructions



System maps out set of virtual neurons and assigns random values or weights to connections – weight determines how each stimulated neuron responds to a digitized feature and adjusted until system responds correctly

Layering: first layer learns primitive features by finding pixel combinations that occur more often than should by chance then feeds to next layer on recognized features learned – repeated

Google produces an image of a cat: 10 million randomly selected videos with cats along with other subjects – used 16000 processors for parallel processing – 16% success rate

Deployed on android voice search resulted in 25% reduction in errors

Deep mind = software that can learn using a deep learning method (reinforcement learning)

# SINGULARITY

"BY 2029, I BELIEVE  
WE WILL HAVE COMPUTERS  
THAT WILL BE  
INDISTINGUISHABLE  
FROM HUMAN INTELLIGENCE  
IN TERMS OF THE  
TURING TEST."

RAY KURZWEIL



<http://singularity.com/>

Concept introduced by Ray Kurzweil in "The Singularity is Near"

When humans and machines merge – "one in which humans gained near immortality by becoming one with robotic technology" [Why the Future Doesn't Need Us: Bill Joy: Wired Magazine August 2000]

Jaron Lanier refers to the Singularity as being like the Rapture in that it cannot be verified by the living. He makes the point in Apocalypse of Self-Abdication that information is an artifact of human thought (much like Jens-Erik Mai).

Bill Joy, creator of Java and Jini, was so disturbed by its line of thinking that he wrote "The Future Does Not Need Us" for Wired magazine (2000)

A recent article (Dec 2015) from Technology Review [<https://www.technologyreview.com/s/544606/can-this-man-make-ai-more-human/>] that claims AI will need to "learn" like children, by example and also by storing, manipulating and applying rules and making conclusions achieved through experience.

# The Singularity

When humans and machines merge

Concept introduced by Ray Kurzweil in “The Singularity is Near”

6 Epochs of Evolution

- Physics & Chemistry
- Biology
- Brains
- Technology
- Merger of Technology & Human Intelligence
- Universe Integration



<http://singularity.com/>

E1: Physics and chemistry: information in atomic structures

E2: Biology: information in DNA

E3: Brains: Information in neural paths

E4: Technology: Information in hardware and software design

E5: Merger of Technology & Human Intelligence: methods of biology (including human intelligence) are integrated into the (exponentially expanding) human technology base

E6: Universe Wakes Up: Patterns of matter and energy in the universe become saturated with intelligent processes and knowledge

## Gelernter (2016)

Tides of Mind: Uncovering the Spectrum of Consciousness

Key question going unanswered: What is the human mind without the human being?

The human mind is not just creation of thought and collection of data; also a product of feelings, composite of sensations, memories, ideas that are worked and reworked over a lifetime.



Computer science Yale University  
Artist and writer

<http://time.com/4236974/encounters-with-the-archgenius/>

Discussion Question

# IS EMBODIMENT A CRITICAL COMPONENT OF EXPERIENCE



# PERSONALIZATION: USER DATA SET



In 2002, Google acquired personalization technology Kaltix and founder Sep Kamver who has been head of Google personalization since. Defines personalization: “product that can use information given by the user to provide tailored, more individualized experience”

## Query Refinement

- System adds terms based on past information searches
- Computes similarity between query and user model
- Synonym replacement

Dynamic query suggestions - displayed as searcher enters query

## Results Re-ranking

- Sorted by user model
- Sorted by Seen/Not Seen

## Personalization of results set

## Calculation of information from 3 sources

- User: previous search patterns
- Domain: countries, cultures, personalities
- GeoPersonalization: location-based results

## Metrics used for probability modeling on future searches

- Active: user actions in time
- Passive: user toolbar information (bookmarks), desktop information (files), IP location, cookies

# Privacy Paradox

Privacy risk is weighed against value of object, interaction, end result

- Research assumes user calculates an internalized value
- Basis for choice to reveal personal identification information (PII)

Value is determined by the smoothness of the interaction (Groupon, Amazon Local)

- Value proposition overrides security/privacy concerns

Higher level of user control over PII reduces the perception of risk



Personalization Privacy Paradox: An exploratory study of decision making process for Location-aware marketing: Xu, Luo, Carroll, et.al.

Study focused on location-aware marketing (LAM) – targeting ads, groupons based on awareness of user location, preferences, etc.

Users share private information in exchange for some THING of perceived value and based on assumptions

Agency will deliver (paper, goods, etc.)

They will not share the information indiscriminately

Will protect the data

Users assume a social contract on the part of the agency that they will be responsible

The ease of usability influences the willingness to proceed – Obama campaign online voter registration 2008 – long form split into small, digestible chunks

Previous privacy risk is more influential in covert model (e.g. tracking without user awareness)

# Google on Privacy

“There was a small trade off on privacy but they’re going to get dramatically better search results. That was something that made sense to us over time.”

Melissa Mayer  
VP User Experience  
Google



[www.google.com/history](http://www.google.com/history)

Web history tied to the Google toolbar (first launched in 2000) and the ability to track what user looked at across the Web

# Google Personalization

## Tracks

- What is selected
- Level of interaction
- What is not-done (bounce rate)

## Signals

- Location  
Search history

Less specific queries benefit the most as they require the additional context provided by personalization



Metrics used for probability modeling on future searches

- Active: user actions in time
- Passive: user toolbar information (bookmarks), desktop information (files), IP location, cookies

In 2002, Google acquired personalization technology Kaltix and founder Sep Kamver who has been head of Google personalization since

Defines personalization: “product that can use information given by the user to provide tailored, more individualized experience”

Personalization enables shorter, less specific queries set to change user behavior (easier, more natural queries) = search shorthand

Tied direct user interaction with results (ability to promote/demote in results set, add comment) discontinued because too noisy & interest did not always equal searching for topic and used by SEO community for other purposes

- Only enable if signed in
- Only impacted future searches (if signed in)

T

# Google Collected Data Types

MICRO: collected over milliseconds

MACRO: data collection over time

MESO: Collected over minutes



## MICRO:

Eye tracking

Visual complexity study showed that users make a decision on attractiveness of a website within 17 milliseconds

Used for feature optimization

## MACRO:

Search logs, user profiles

Aggregated over time

Used to learn about search strategies over time

## MESO:

Ethnographic studies

Field studies

Hands on user studies

Used to learn about search behavior and habits

# What Google Collects

Profile information

Use information

Device information

Log information

Location information

Unique application information

Local storage

Cookie data



Google Privacy Policy <http://www.google.com/policies/privacy/shared-across-services>

- Profile information: Information you give us. For example, many of our services require you to sign up for a Google Account. When you do, we'll ask for personal information, like your name, email address, telephone number or credit card. If you want to take full advantage of the sharing features we offer, we might also ask you to create a publicly visible Google Profile, which may include your name and photo.
- Use information: Information we get from your use of our services. We may collect information about the services that you use and how you use them, like when you visit a website that uses our advertising services or you view and interact with our ads and content. This information includes:
- Device information: We may collect device-specific information (such as your hardware model, operating system version, unique device identifiers, and mobile network information including phone number). Google may associate your device identifiers or phone number with your Google Account.
- Log information "When you use our services or view content provided by Google, we may automatically collect and store certain information in server logs. This may include:
  - details of how you used our service, such as your search queries.
  - telephony log information like your phone number, calling-party number, forwarding numbers, time and date of calls, duration of calls, SMS routing information and types of calls.
  - Internet protocol address.
  - device event information such as crashes, system activity, hardware settings, browser type, browser language, the date and time of your request and referral URL.
  - cookies that may uniquely identify your browser or your Google Account.
- Location information: When you use a location-enabled Google service, we may collect and process information about your actual location, like GPS signals sent by a mobile device. We may also use various technologies to determine location, such as sensor data from your device that may, for example, provide information on nearby Wi-Fi access points and cell towers.
- Unique application numbers" Certain services include a unique application number. This number and information about your installation (for example, the operating system type and application version number) may be sent to Google when you install or uninstall that service or when that service periodically contacts our servers, such as for automatic updates.
- Local storage: We may collect and store information (including personal information) locally on your device using mechanisms such as browser web storage (including HTML 5) and application data caches.
- Cookies and anonymous identifiers: We use various technologies to collect and store information when you visit a Google service, and this may include sending one or more cookies or anonymous identifiers to your device. We also use cookies and anonymous identifiers when you interact with services we offer to our partners, such as advertising services or Google features that may appear on other sites.

# User Profile

## Information types

- Demographic
- Interests (short & long-term)
- Preferences

## Two types of collection

- Explicit
- Implicit

## Dynamic profiles iterate over time

## Represented as

- Set of weighted keyword
- Weighted concepts
- Semantic network



## User profile phases

1. Gather raw information
2. Construct profile from user data
3. Allow application to exploit profile to construct personal results

## Keywords profiles represent areas of interest

- Extracted from documents or directly provided by user, weights are numerical representation of user interest
- Polysemy is a big problem for KW profiles

## Semantic networks

### Filtering system

Network of concepts – unlinked nodes with each node representing a discrete concept

Used by alta vista (used header that represented user personal data, set of stereotypes (prototypical user comprised of a set of interests represented by a frame of slots

Each “slot” (made up of domain, topic & weight (domain =area of interest, topic = specific term used to identify area of interest, weight = degree of interest) that makes up frame weighted for relevance

# Methods

Client Side: gather data from user profile

Server Side: gather data from system usage (logs)

Groupization: Recommender system with vested interest

- Group member data used to rank the individual results
- Relevance weigh enhanced with more members of group who “like” resource
- Sum of personalization scores of each group member



Source: Information Retrieval: Personalization 2 Fernando Diaz Yahoo! Labs April 25, 2011

Use group level information rather than individual  
Groups intersect with work or social interests (or both)

Advantages: can protect group privacy, potentially richer user signals  
Disadvantages: no external data used, client side resource challenges (processing/space)

# Implicit Collection

## Implicit (max precision 58%)

- Software agents
- Logins
- Enhanced proxy servers
- Cookies
- Session IDs

## Gathered without user awareness from behavior

- Query context inferred
- Profile inferred
- Less accurate
- Requires a lot of data



Jaime Teevan MS Research

[http://courses.ischool.berkeley.edu/i141/f07/lectures/teevan\\_personalization.pdf](http://courses.ischool.berkeley.edu/i141/f07/lectures/teevan_personalization.pdf)

Tools used

Software agents: most reliable as more control over install and application

Cookies: least invasive

Login: more pervasive across machines and time

Proxy Servers: limited to user register of machine with server

Session IDs: limited to a single session

Advantages: more data, better data (easier for system to consume and rationalize)

Disadvantage: user has no control over what is collected

# Explicit Collection

Explicit (max precision 63%)

- HTML forms
- Explicit user feedback interaction (early Google personalization with More Like This)

Provided by user with knowledge

More accurate as user shares more about query intent and interests



Advantage: User has more control over personal and private information

Disadvantage: compliance, users have a hard time expressing interests, burdensome on user to fill out forms, false info from user

# Context

Context becomes what the system can measure

- Environmental features
- Interactions
- Ubiquitous computing
- Internet of things (IoT)

Non-methodical approach that brings in  
containment (social through local) interactions

- Adaptive/reactive interaction in situ
- Context as perceived and used by actor



# AI ETHICS & SAFETY



# Adversarial AI

Used in adversarial setting

Used for malicious means



Adversarial setting example: Russian hacking of US election

Malicious means: Fall 2016 IoT hack that took down part of the internet

## 3 Laws of Robotics

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm
2. A robot must obey orders give in to it by human beings except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Law.



Isaac Asimov in I, Robot

# St Thomas Symposium (2004)

Need synthesis of methodologies

Move from reactive to deliberative thinking

Include affective concepts like emotions

- Primary
- Secondary
- Tertiary

Incorporate “common sense” thinking

Source of human resourcefulness and robustness



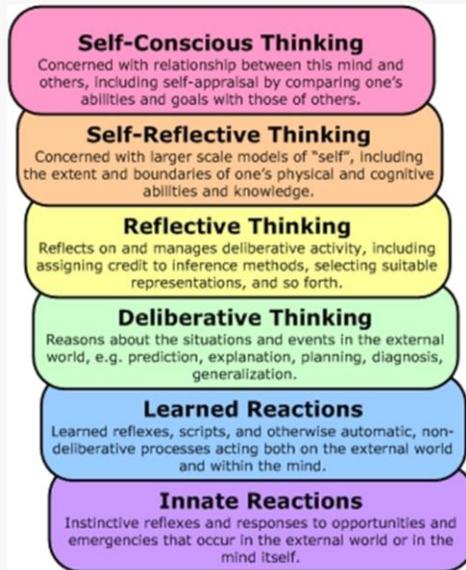
Designing Architectures for Human Level Intelligence - St Thomas VI 2004

Marvin Minsky MIT

Push Singh MIT

Aaron Sloman University of Birmingham UK – Cognition and Effects project

# Sloman Minsky Model (2000)



Levels of control

Emphasizes the role of motives (generally distinguished from emotions) – motives have both emotional and cognitive correlates

Emotional Machine Architecture

<http://www.aai.org/ojs/index.php/aimagazine/article/view/1764/1662>

Human level intelligence requires a machine architecture that can support multiple ways to represent | acquire | apply common sense knowledge

Requirements

- Development of an “intention-based” programming languages
- Vigilance for programmer bias
- Virtual model world
- Develop and organize mini scenarios
- Organize and evaluate progress
- Create interoperable protocols
- Catalogue all “ways to think” (reasoning about prediction, explanation, generalization, exemplification, abstraction)
- Debug learning

# Asilomar Conference 2009



<http://www.aai.org/Organization/presidential-panel.php>

Called together computer scientists to consider AI successes, address changes and opportunities in light of the success.

Reflect on potential socioeconomic, legal and ethical issues surrounding machine intelligence

Review concerns about control of computer-based intelligences

Consider proactive actions that could enhance long-term societal outcomes

Participants: Margaret Boden, Craig Boutilier, Greg Cooper, Tom Dean, Tom Dietterich, **Oren Etzioni (UW, Allen Institute of Brain Science)**, Barbara Grosz, **Eric Horvitz (Microsoft technical Fellow)**, Toru Ishida, Sarit Kraus, Alan Mackworth, David McAllester, Sheila McIlraith, Tom Mitchell, **Andrew Ng (Baidu)**, David Parkes, Edwina Rissland, Bart Selman, Diana Spears, Peter Stone, Milind Tambe, Sebastian Thrun, Manuela Veloso, David Waltz, Michael Wellman

# Asilomar AI Research Needs: HCI

## Research Needs

- Assess the risk of AI Chain Reaction
  - Test the hypotheses underlying the Singularity vision
- Research on HCI for humans interacting with (and relying upon) AI systems
  - Explanation, transparency, control, trust



Source: Asilomar Study on Long-Term AI Futures: Highlights of 2008-2009 Study: Presidential Panel on Long-Term AI Futures IJCAI 2009 Invited Panel, July 2009

# AI Risks

Mis-specified Objectives

Negative Side Effects that extend to wider application

Hacking: rewards, devices

Bad extrapolation of the real world

Poor training data

Privacy

Fairness

Abuse

Transparency



Google Report on AI Safety

Privacy: right to be forgotten

Fairness: digital divide

Security: IoT takedown of internet, GM self-driving car

Transparency: common understanding of complex engineering

# AI Risk Mitigations

## Define impact regulator

- Future state
- Substitutes lower impact null actions

## Train impact regulator

- Over many tasks
- Separate training parameters for task side effects

## Penalize influence

- Use information-theoretic measures to capture agent's potential for information
- Penalize empowerment

## Scalable oversight with multi-agent approach



Multi-agent approach = human and agent working together

Reward Hacking: adversarial reward function, careful programming to avoid adversarial blindness

Scalable oversight: distant supervision, hierarchical reinforcement learning

## AI Risk Mitigations 2

Use Objective functions to capture designer informal intent

- No partially observed goals
- Concrete, not abstract rewards
- Deep correlation between tasks and functions

Feedback loops

- Model look ahead
- Reward capping
- Counter example resistance – combination of rewards



Correlation between tasks and rewards: do not base cleaning robot reward on amount of cleaning supplies used

# AI Risk Mitigations 3

## Safe exploration

- Risk sensitive performance criteria
- Use demonstration
- Simulated exploration

## Well defined models

- Train on multiple distributions
- Program for out-of-distribution situations



Simulated exploration: bounded exploration, trusted policy oversight, human oversight

## Stanford 100 Year AI Study (2016)

Long term reoccurring study of AI influence on people and society

Modeled after Association for Advancement of Artificial Intelligence (AAIA) consortium 2008

4 intended audiences

- General public
- Industry
- Government
- AI Researchers



AAAI organized by Eric Horvitz – AI experts along with scholars from cognitive science, philosophy and law

Salient Domains: transportation, service robots, healthcare, education, low-resource communities, public safety and security, employment and workplace and entertainment

Discussion Question

## **ARE THE TRADE-OFFS WORTH IT?**



# THE IA OF AI



# AI Design According Computer Science

## Components

- Variables
- Domains (environment)
- Constraints (limits)

Goal of AI Design = satisfy constraints

Admissible heuristic: if it costs too much to reach solution state then revise or reject



## AI and Design

Krzysztof Gajos

Harvard University CS 182, Fall 2011

<http://isites.harvard.edu/fs/docs/icb.topic958294.files/CS%20182%20-%20AI%20and%20Design%20-%202011.pdf>

# Information Architecture and AI

Site Structure

Connections

Proto-typicality (mental models)

Visual complexity (text over images)



Legacy newspaper structure of “the fold.”

Proto-typicality: user mental models

Visual complexity: ratio of images to text favors text

# Navigation

Users need inducement to move further into the site

User focus has changed from navigation to search



Information Architecture: Structure is the Search Aphrodisiac

Distance reflects relevance

URL Depth: the further from the homepage, the less important it must be

Click Distance: the further from an authority page, the less important it must be

Page Structure Now a Factor

Google Page Segmentation Patent: Determining Semantically Distinct Regions of a Document

Based on eye-tracking studies and user behavior

Similar Yahoo patent

# Enhanced Navigation

Machine readable text  
Related content model  
Schema markup



Put the sidewalks where the footprints are  
Resource: Stuart Brand: How Buildings Learn

# Too Many Choices

Search

Treatment Ratings Find a Doctor Ask a Doctor Write a Review

## Brazilian Butt Lift [Write a Review](#)

[Reviews \(3236\)](#) [Photos \(821\)](#) [Q&A \(2050\)](#) [Forum \(687\)](#) [Guides](#) [Doctors](#)

**93%**   
WORTH IT RATING  
based on 3236 stories

In a Brazilian Butt Lift (BBL), your surgeon takes fat from where you don't want it and injects it in your butt to give you that envy-worthy Hollywood rear view. [Read More »](#)

Average Price: \$7,075

## Reviews from the Community

Narrow by:

Rating  Weight  Ethnicity  Post-Op

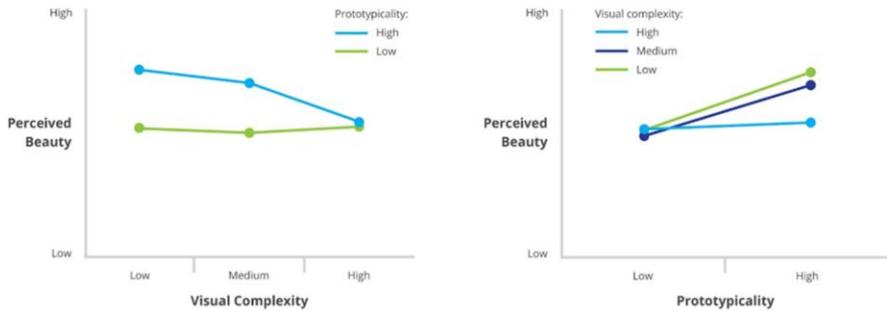
Sort by: » [Best Match](#) | [Recent](#) | [Nearby](#) | [Comments](#)

3236 results



93

# Visual Complexity & Prototypicality

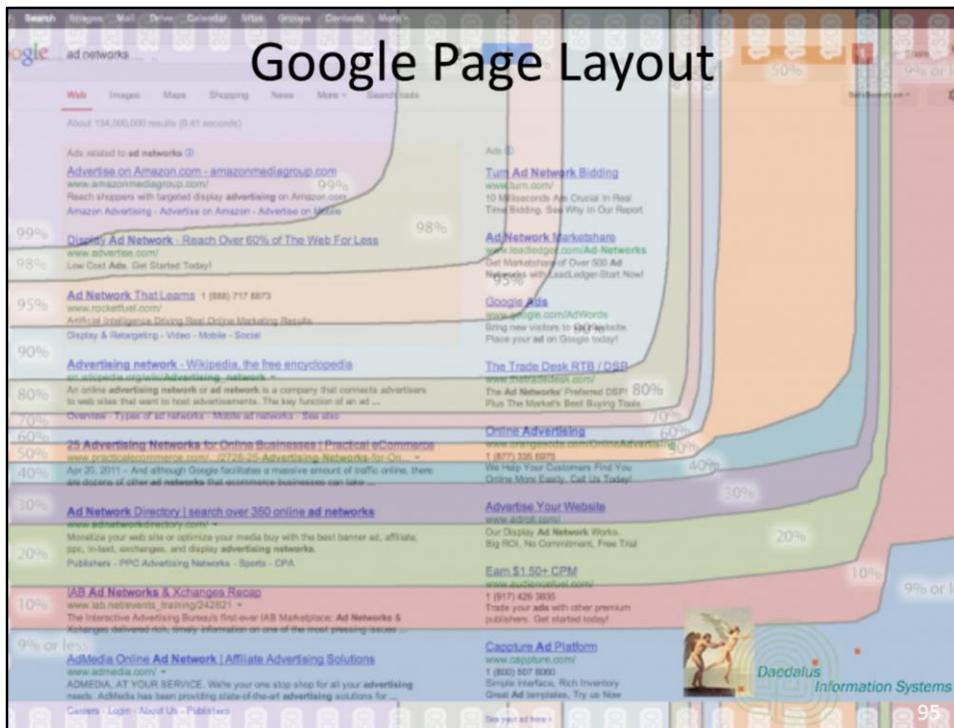


## VISUAL COMPLEXITY & PROTOTYPICALITY

The results show that both visual complexity and proto-typicality play crucial roles in the process of forming an aesthetic judgment. It happens within incredibly short timeframes between 17 and 50 milliseconds. By comparison, the average blink of an eye takes 100 to 400 milliseconds.

In other words, users strongly prefer website designs that look both *simple* (low complexity) and *familiar* (high prototypicality). That means if you're designing a website, you'll want to consider both factors. Designs that contradict what users typically expect of a website may hurt users' first impression and damage their expectations.  
August 2012

Resource: <http://googleresearch.blogspot.com/2012/08/users-love-simple-and-familiar-designs.html>



From Patent: Techniques for approximating the visual layout of a web page and determining the porting of the page containing significant content.

“As we’ve mentioned previously, we’ve heard complaints from users that if they click on a result and it’s difficult to find the actual content, they aren’t happy with the experience. Rather than scrolling down the page past a slew of ads, users want to see content right away. So sites that don’t have much content “above-the-fold” can be affected by this change.”

<http://googlewebmastercentral.blogspot.com/2012/01/page-layout-algorithm-improvement.html>

#### Resources

<http://www.seobythesea.com/2011/12/10-most-important-seo-patents-part-3-classifying-web-blocks-with-linguistic-features/>

<http://www.seobythesea.com/2008/03/the-importance-of-page-layout-in-seo/>

# THE UX OF AI



## What is the ISO Definition of UX?

A person's perceptions and responses that result from the use or anticipated use of a product, system or service.



Draft definition

## How UX Professionals Defined UX?

A consequence of a user's internal state (predispositions, expectation, needs, motivations, mood, etc.) the characteristics of the designed system (e.g. complexity, purpose, usability, functionality, etc.) and the context (or the environment) within which the interaction occurs (e.g. organization/social setting, meaningfulness of activity, voluntariness of use, etc.)



Understanding, Scoping and Defining User Experience: A Survey Approach: Law, Roto, Hassenzahl, Vermeeren, Kort (CHI 2009)

No shared, clear definition of User Experience

- UX is associated with broad/fuzzy concepts that encompass emotion, hedonic, aesthetic, experiential values
- Units of measure are too squishy (quantitative more than qualitative)
- UX discipline is influenced by too many and too diverse theoretical models (again too squishy)

Survey of UX professionals picked this definition

# Panda Algorithm Negative Signals

- High % of deep content
- Low amount of original content
- High amount of ads or gratuitous images
- Large quantity of boiler-plate text
- Over-optimized (too many links)
- High bounce rate
- Low visit duration
- Low CTR from Google search results
- No/Low quality in-links
- No/Low social mentions



February 2011

Multiple updates over the ensuing years

Focused on getting rid of “low quality” or “thin sites” so that high quality sites are at the top of the results

# User Metrics Training Data

Frequency of access

Click-through (selection from results set)

Time on site

Pages per session

Bounce Rate

Conversion (fulfilled information need)

Profile data



## Why Google Focused on UX for Ranking

Silo-i-zation of Web design and development

Fragmentation of UX community

UX lack of interest in SEO



Google does not care about UX (just look at android)

Like it or not, part of Google's evil strategy in selecting the UX community is because they think that we have our heads in the clouds.

# Key UX Data Points

Conversions

Unique Visitors

Bounce rate

Social Actions

Number of Pages/visited

Average time on page (exclude bounces)

Exit rate



# THE CONTENT STRATEGY OF AI



## It All Starts With TF\*IDF

The tf-idf weight of a term is the product of its tf weight and its idf weight.

$$w_{t,d} = \log(1 + \text{tf}_{t,d}) \times \log_{10}(N / \text{df}_t)$$

**Best known weighting scheme in information retrieval**

Note: the “-” in tf-idf is a hyphen, not a minus sign!

**Alternative names: tf.idf, tf x idf**

Increases with the number of occurrences within a document

**Increases with the rarity of the term in the collection**



$t$  = how many times the query appears in a document

$T$  = total number of terms in a document

$D$  = set of all documents

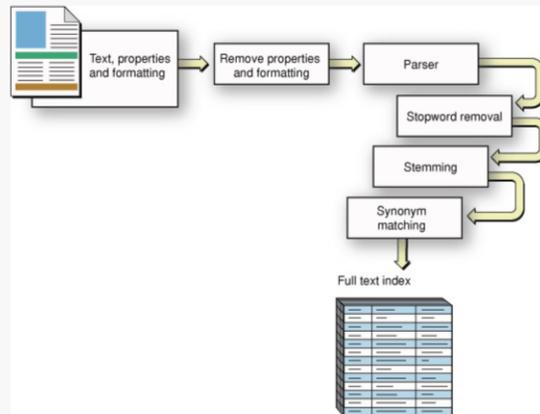
$d$  = number of documents with that term

Highest score wins!

The document with the highest proportion of terms which are part of the query is most relevant

- Documents containing more of the term(s) scored higher
- Longer documents discounted
- Rare terms weighted higher

# Text Processing by Algorithm



- Notes formatting
- Removes stop words
- Stems (reduces to base grammatical concept)
- Matches synonyms



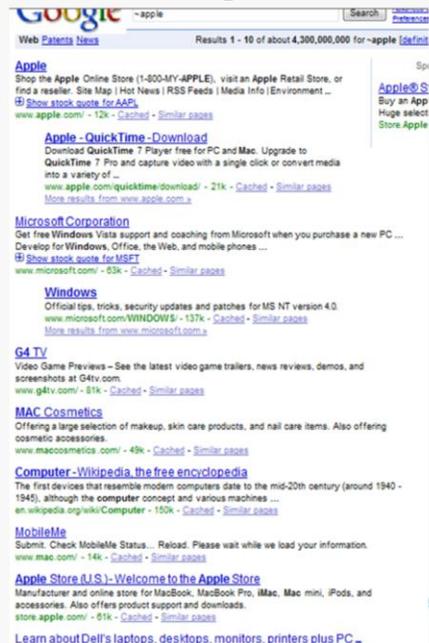
Minimum term length – eliminate stop words (generally articles, and, if, the, but an, or...) and those too short (unlikely candidates for search)

Synonyms: manually done for smaller indexes, LSI for Web search engines

Stemming: reduces to most basic root, also known as lemmatization, some use of n-grams (**n-gram** is a contiguous sequence of  $n$  items from a given sequence of text or speech, can be syllables, letters, words or base pairs collected from corpus)

# Latent Semantic Indexing

Using a ~<search term> will initiate Google's LSI and produce a list of results that contains your original term as well as documents that the search engine determines are relevant to your query.



Uses single value decomposition to determine relationships between terms and concepts

- In linear algebra, the singular value decomposition (SVD) is a factorization of a real or complex matrix

Appropriate to Boolean model

First application in 1980's at Bell Laboratories

Sandboxed on Google in mid2000's

In example:

There are no listings for "apple" the fruit – the search engine has been trained to associate "apple" singular with the computer company

The #2 result is Microsoft – the search engine has been trained to associate the term Apple with Microsoft

The #4 result is for Mac cosmetics because the search engine does not know the difference between Mac computers and Mac mascara.

# Convey UX

Keyword	Repeats	Wizard	Density	Prominence
view profile	6 A		1.58%	58
cory doctorow	5 H,A,IA		1.32%	60
session videos	5 A,LI		1.32%	92
michael gough	4 H,A,I			
amber case	3 H,A,I		0.79%	36
joe welinske	3 A		0.79%	77
conveyux conference	3 T,A,I		0.79%	60
video posted	3 H,A		0.79%	36
session preview				
video posted brad weaver	2 H,A		1.05%	36
weaver on cinematic ux	2 H,A		1.05%	36
brad weaver on cinematic	2 H,A		1.05%	36
peter merholz			0.79%	30
quantifying delig				
brad weaver	Phrases 5			
mary haggard				
posted brad weaver on cinematic	2 H,A		1.32%	36
brad weaver on cinematic ux	2 H,A		1.32%	36



# HITS (1997)

Hypertext Induced Topic Search

HITS is a related algorithm for Authority determination

HITS = PageRank + Topic Distillation

Unlike PR, query dependent

Somewhat recursive



Jon Kleinberg – CS Professor at Cornell

Simultaneous development to PR (HITS is query dependent). PageRank its sibling using another facet of academia: citation chaining

Calculates: root set, outlinks and inlinks, results in focused neighborhoods (sub graphs) , calculates authority weight (Distillation of broad search topics with authority and Hubs (pages that links to many authority pages on topic)

- Define topics
- Detect authorities
- Detect hubs

Web emerging with pages that were access points to other pages on particular topic

Uses hubs and authorities to define a recursive relationship between web pages

An authority is a page that many hubs link to

A hub is a page that links to many authorities

Subset analysis of link graph to split out topics, then authority pages, then hub pages that consolidate links to authority pages on the topic

Collect top ## of results (based on occurrences) = root set

Construct a small link graph with pages pointing to pages in root set

Collect set of pages that either link to authority pages in set or are included in hubs

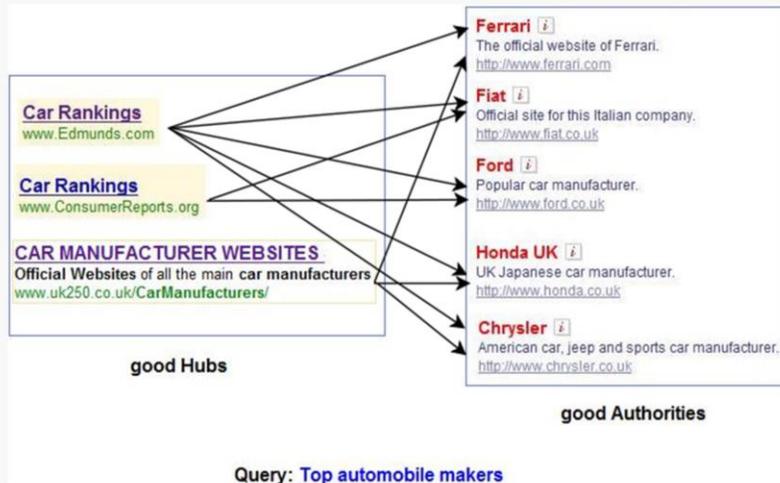
that link to pages in set

*“HITS algorithm is in the same spirit as PageRank. They both make use of the link structure of the Web graph in order to decide the relevance of the pages. The difference is that unlike the PageRank algorithm, HITS only operates on a small subgraph (the seed SQ) from the web graph. This subgraph is query dependent; whenever we search with a different query phrase, the seed changes as well. HITS ranks the seed nodes according to their authority and hub weights. The highest ranking pages are displayed to the user by the query engine.”*

<http://www.math.cornell.edu/~mec/Winter2009/RalucaRemus/Lecture4/lecture4.html>

Recursive in that good authorities receive links from good hubs link out to good authorities

# Authorities & Hubs



<http://www.math.cornell.edu/~mec/Winter2009/RalucaRemus/Lecture4/lecture4.html>

Authority Score is based on Web link structure (using representational sample set of WWW pages to distill structure)

Hubs: WW form of biblio-metrics – collection of thematically related authority pages

# Hilltop Algorithm (2001)

Topic segmentation algorithm = query dependent

Introduces concept of non-affiliated “expert documents” to HITS

Quality of links more important than quantity of links

Segmentation of corpus into broad topics

Selection of authority sources within these topic areas



“Our approach is based on the same assumptions as the other connectivity algorithms, namely that the number and quality of the sources referring to a page are a good measure of the page's quality. The key difference consists in the fact that we are only considering "expert" sources - pages that have been created with the specific purpose of directing people towards resources.”

<http://ftp.cs.toronto.edu/pub/reports/csr/405/hilltop.html>

## Components

Quality of links more important than quantity of links

Only links from Segmentation of corpus into broad topics

Subset that is then extrapolated to Web as a whole

Selection of authority sources within these topic areas with authorities have lots of unaffiliated expert document on the same subject pointing to them

Hubs are navigation pages that point to several authority resources on a certain topic

HITS is a related algorithm for Authority determination

The beauty of Hilltop is that unlike PageRank, it is query-specific and reinforces the relationship between the authority and the user's query. You don't have to be big or have a thousand links from auto parts sites to be an “authority.”

## Topic-Sensitive PageRank (2002)

Context sensitive relevance ranking based on a set of “vectors” and not just incoming links

Pre-query calculation of factors based on subset of corpus

Context of term use in document

Context of term use in history of queries

Context of term use by user submitting query

Based on 16 top-level Open Directory categories



PR: single vector computed to capture relative importance + set of vectors based on document topics = TSPR

Instead of the single PR vector TSPR uses a set of ranking vectors: Pre-query selection of topics + at-query comparison of the similarity of query to topics

Topic-Sensitive PageRank computes PR based on a set of representational topic vectors  
Augments PR with content analysis

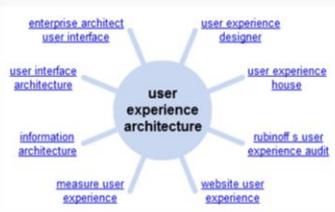
At query time, calculates similarity of query to the topics

Computes PR based on a set of representational topics [augments PR with content analysis], rank vectors determine importance

Topic specific vectors derived from the 16 top-level categories from the Open Source directory (pre-query processing done offline)

Top-level categories (from Wikipedia): *Adult, Arts, Business, Computers, Games, Health, Home, News, Recreation, Reference, Regional, Science, Shopping, Society, Sports* and "World".

# Orion Algorithm (2008)



**Purchased by Google in April 2006 for A LOT of money**

**Results include expanded text extracts from the websites**

**Integrates results from related concepts into query results**

**Related searches**

Related searches for **user experience architecture**:

<a href="#">measure user experience</a>	<a href="#">information architecture</a>	<a href="#">architecture user experience design</a>
<a href="#">rubinoff s user experience audit</a>	<a href="#">usability architecture</a>	<a href="#">customer experience architecture</a>
<a href="#">website user experience</a>	<a href="#">ux architecture</a>	<a href="#">user experience art</a>
<a href="#">user experience house</a>	<a href="#">interaction design architecture</a>	<a href="#">user experience interior design</a>
<a href="#">user experience application</a>	<a href="#">ui architecture</a>	<a href="#">user experience architecture oriented</a>

**User experience design** - Wikipedia, the free encyclopedia  
 User experience design is a subset of the field of experience design that pertains to the creation of the architecture and interaction models that impact ...  
 The designers - The design - Benefits - See also  
[en.wikipedia.org/wiki/User\\_experience\\_design](#) - Cached - Similar

**How To Quantify The User Experience**  
 How can you quantify a concept as nebulous as user experience? ... used because it's buried deep within the bowels of the site's information architecture. ...  
[articles.sitepoint.com/article/quantify-user-experience](#) - Cached - Similar

**Kevin Mattice — User Experience Architect**  
 Kevin Mattice, user experience architect, is a former Air Force intelligence analyst and Gulf War veteran whose entire career has been oriented around the ...  
[kevinmattice.com/](#) - Cached - Similar



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<http://googleblog.blogspot.com/2009/03/two-new-improvements-to-google-results.html>

Developed by a computer science student, this algorithm was the subject of an intense bidding war between Google and Microsoft that Google one. The student, Ori Allon, went to work for Google in April 2006 and has not been heard from since. There is no contemporary information on the algorithm or it's developer.

Allon left Google in 2010 to found Julpan, social network analysis tool acquired by Twitter (analyzes social activity for what is being shared)

Relational content modeling done by machines-usually contextualized next steps.

<http://searchengineland.com/google-implements-orion-technology-improving-search-refinements-adds-longer-snippets-17038>

*Orion finds pages where the content is about a topic strongly related to the key word. It then returns a section of the page, and lists other topics related to the key word so the user can pick the most relevant.*

*“The results to the query are displayed immediately in the form of expanded text extracts, giving you the relevant information without having to go the website—although you still have that option if you wish,” said Israeli-born Allon, who completed a Bachelor and Masters degree at Monash University in Melbourne before moving to UNSW for his PhD. By displaying results to other associated key words directly related to your search topic, you gain additional pertinent information that you might not have originally conceived, thus offering an expert search without having an expert’s knowledge.*

# Hummingbird: Entity detection

Comparison of search query to general population search behavior around query terms

Revises query and submits both to search index

- Confidence score
- Relationship threshold
- Adjacent context
- Floating context
- Results a consolidation of both queries



Entity=anything that can be tagged as being associated with certain documents, e.g. Store, news source, product models, authors, artists, people, places thing

The entity processing unit looks at “candidate strings and compares to query log to extract: most clicked entity, most time spent by user)

Referring queries data taken away

User Behavior information: user profile, access to documents seen as related to original document, amount of time on domain associated with one or more entities, whole or partial conversions that took place

# AI Content Components

Traditional IR (tf\*idf)  
Link analysis  
Page Layout  
Query type  
Uniqueness  
Authoritative  
Freshness  
Well Written



Link analysis (matches context of query)

Page layout (content above fold, not too many ads/images)

Authority (site and author)

Query Type: Informational queries account for 63% of studied with transactional at 22% and navigational at 15%

Well written: Fleishman Kincaid scale, grammar and spelling

# Content Creation | Curation

Dense, subject-specific content is what is indexed

Opening paragraphs most important for subject determination

Newspaper model

Trim the garden: get rid of the old or unpopular items



Home page

The more content, the stronger the representation in the search engine index

More content = Authority = aboutness

People will scroll - If they don't scroll, they will print it out

Visible text on a page is what counts

Spiders cannot "see" = cannot read text images

Consistency in terminology and emphasis in topicality on page is good however search engines are sensitive to over optimization

Headings are a user's and the spider's friend. Extra credit for having them and for having topic terms in there

Search engines are:

Semantic (LSI)

Judgmental

Evaluate content based on non-content criteria (bounce rate, click through, conversion)

# DESIGN FOR AI



<https://www.oreilly.com/learning/machine-learning-for-designers>

Human-centered design has expanded from the design of objects (industrial design) to the design of experiences (encompassing interaction design, visual design and the design of spaces). The next step will be the design of system behavior; the design of algorithms that determine the behavior of automated intelligent systems

Harry West  
CEO, Frog Design



# Machines As Users Are Different

Logic: exacting, context independent,  
conditional logic

Development: uses explicit rules to define  
possible behaviors

- Heuristics
- Intuition derived from huge data sets



# Reasoning

## Deductive

Theory  
Hypothesis  
Observation  
Confirmation

## Inductive

Theory  
Hypothesis  
Pattern  
Observation



# Design Thinking for Data Science 1

Reach out to the development staff

Embrace design thinking

Transform “my idea” into “our idea” with early stage collaboration



<https://www.linkedin.com/pulse/design-thinking-data-science-george-roumeliotis>

<http://www.intuitlabs.com/page/2/?s=design+for+delight>

# Design Thinking for Data Science 2

## Customer Empathy Stage

- Understand the problem solving
- Define the solution
- Map the environment (customer journey)
- Define the characteristics of a good solution (heuristics)

## Outputs

- Personas (use cases)
- Problem statements
- Environment description (include systems and processes)
- Benchmark success (quantitative, qualitative)



<https://www.linkedin.com/pulse/design-thinking-data-science-george-roumeliotis>  
<http://www.intuitlabs.com/page/2/?s=design+for+delight>

## Design Thinking for Data Science 3

Go Broad, Go Deep Stage

Brainstorm solution ideas across silos

Diversify contributors

Post all artifacts and review as a group

Organize ideas into themes

Include “leap of faith” assumptions

Take the best and formulate a solution hypothesis



<https://www.linkedin.com/pulse/design-thinking-data-science-george-roumeliotis>

<http://www.intuitlabs.com/page/2/?s=design+for+delight>

# Design Thinking for Data Science 4

Rapid experimentation with Customers

Paper prototyping, sketches, storyboard

Build stable testing methodology into plan

Start small (project | testing) to achieve  
collective wins



# Algorithm-Based Design 1

Designer as art director, algorithm as apprentice

Determine “well designed” site for learning model

Create mood board for algorithm to deconstruct

Use algorithm for simple tasks

- Color match up
- Image assembly (movie poster app)
- Styling videos
- Extract usage patterns from data sets



<https://www.smashingmagazine.com/2017/01/algorithm-driven-design-how-artificial-intelligence-changing-design/>

## Algorithm-Based Design 2

Designer and Developer define the logic to consider content, context and user data

AEM (behavior targeted UI)

Brightedge DataMind

Vox Media Homepage Generator



<https://www.smashingmagazine.com/2017/01/algorithm-driven-design-how-artificial-intelligence-changing-design/>

Vox generator: algorithm pulls the page layout from pattern library based on user profile, display dictated by # of words, paragraphs, images, inserts

# Generative Design

AKA Mutative Design, Parametric Design

Designer defines rules for algorithm

Algorithm generates variations using the predefined rules

Algorithm filters the results based on design quality and requirements

Designer chooses the best variants and polishes as needed

System runs A|B tests for variant(s)

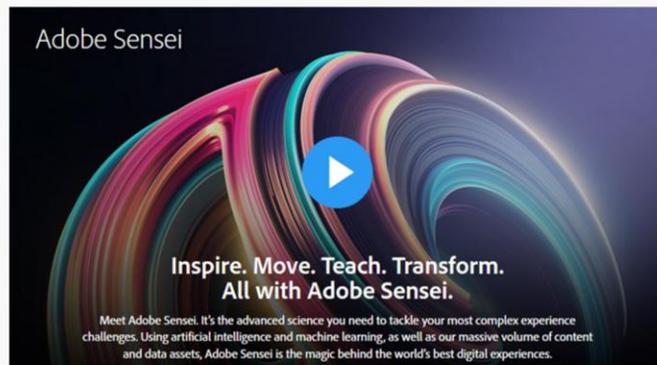
Test results used to choose most effective design



Idealized collaboration  
Iterative  
Zora Hadid Architects

Project Phoebe: mutative design  
<https://medium.com/project-phoebe/meet-project-phoebe-a-moonshot-concept-for-mutative-design-88d997f7ff14#.umwh0ksh3>

## Smart Tools & Platforms



Sensei uses machine learning and artificial intelligence

Semantic image segmentation

Font recognition

Intelligent audience segmentation



<http://www.adobe.com/sensei.html>

# Machine Learning Design Process

## Define learning problem

- Inputs
- Outputs
- Training Data

## Generate good data

- Completeness
- Accurate
- Consistent
- Timely

Sketch out user and data flow (decision trees)

Test assumptions against prototype

Start with simple mechanism and move to complex



Completeness: indicative of a range of possible behaviors

Accurate: true to real world behavior

Consistent: various data points within the set are not contradictory

Timely: relevant to current system state

**IF NOT US, WHO?**



## Why Not Google?

Without a person at (or near) the helm who thoroughly understands the principles and elements of Design, a company eventually runs out of reasons for design decisions... When a company is filled with engineers, it turns to engineering to solve problems. Reduce each decision to a simple logic problem. Remove all subjectivity and just look at the data. Data in your favor?... And that data eventually becomes a crutch for every decision, paralyzing the company and preventing it from making any daring design decisions.



<http://stopdesign.com/archive/2009/03/20/goodbye-google.html>

Douglas Bowman  
on leaving as head of Google Visual Design (2009)

Tested 41 shades of blue

# Prediction Is Not Infallible



AI algorithms rely on past behavior to predict future behavior

Programming and test set must define “normal” for the system to detect “abnormal”



Cannot predict what has not already occurred  
Flash Crash 2009  
Taleb's Black Swans

# Prediction Drawbacks

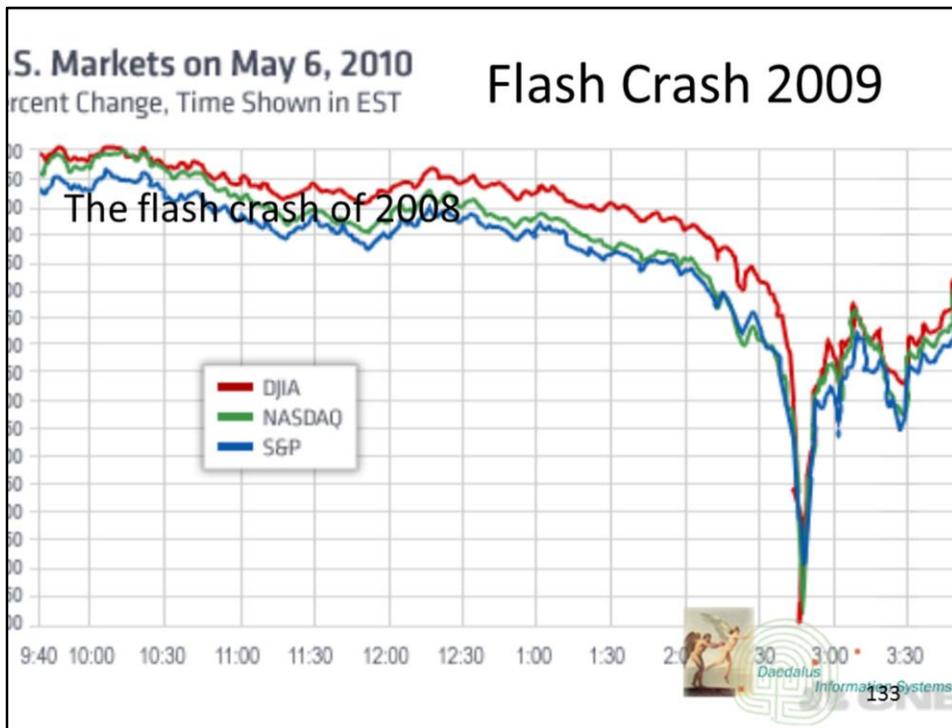
Cannot predict what has not already occurred

- Taleb's black swans
- Flash Crash of 2009

Past behavior prediction ignores present environment and emotional influences

Must define normal to program for abnormal detection





[http://www.ted.com/talks/kevin\\_slavin\\_how\\_algorithms\\_shape\\_our\\_world.html](http://www.ted.com/talks/kevin_slavin_how_algorithms_shape_our_world.html)

Kevin Slavin (Assistant Professor, MIT Media Lab): How algorithms share our world and the Flash Crash of 2010 during which the stock market dropped 1000 points in moments and took with it billions of dollars due to conflicting algorithmic trades.

Algorithms were used to break up big things (huge stock trades) into many little things (individual trades) and then recombine - Flash crash of 2:45 where 9% of entire stock market disappeared - went away - no one can explain because they did not do anything...algorithms did it

Epagogix: story algorithms to predict movie success before writing (Netflix Pragmatic Chaos algorithm influences 60% of rentals)

Elevators where you push floor before getting in and that determines what elevator - inside there are no buttons (so cannot change your mind)

## Learning is one Thing...Thinking Another

“In designing software and microprocessors, I have never had the feeling that I was designing an intelligent machine. The software and hardware is so fragile and the capabilities of the machine to “think” so clearly absent that even as a possibility, this has always seemed very far in the future...***My person experience suggest we tend to over estimate our design abilities.***”



Bill Joy, cofounder Sun Microsystems, creator Java and Jini

## Sometimes They Learn the Wrong Things



**Bill Slawski** @bill\_slawski · 12s

Microsoft unveils a better-behaved chatbot after its last one became a NAZI



**Microsoft unveils a better-behaved chatbot after its last one became ...**

Tech giant takes another pop at the artificial intelligence game with the release of a politer (and slightly stupider) machine mind

135 ems

## You Are Not A Gadget

*“Whenever a computer is imagined to be intelligent, what is really happening is **that humans have abandoned aspects of the subject at hand in order to remove from consideration whatever the computer is blind to.**”*



Cyber-totalitarianism/Digital Maoism: the focus is on abstraction of the network more than the real people that use it. Lanier believes that emphasizing the crowd deemphasizes the individual. He sustained an online debate over this in 2006 (The Edge) where he referenced the “hive mind” or noosphere (collective brain).

Emphasizing the crowd means de-emphasizing the individual

Lanier goes on to observe that instances of intelligence in a machine are ambiguous and that we degrade our sense of personhood to make machine seem more intelligence or capable of learning.

## Lanier on Computationalism

“Context has always been part of expression because expression become meaningless if context becomes arbitrary...meaning is only every meaning(ful) in context.

...

Any gadget, even a bit one like Singularity, gets boring after awhile. But a deepening of meaning is the most intense potential kind of adventure available to us.”



Lanier’s concept of computationalism:

Logical Positivism: a sentence or other fragment that can be put into a computer file will mean something in a freestanding way that does not require invoking the subjectivity of a human reader. EG: a computer can figure out the “meaning” of a sentence if the instructions are correct and comprehensive

World can be understood by computational processes with humans as sub processes

1<sup>st</sup> level: logical positivism

2<sup>nd</sup> level: a compute program with features related to self representation and circular references similar to a person

3<sup>rd</sup> level: an information structure that can be perceived to be human by a human (Turing Test)

# Computationalism Components

World can be understood by computational processes with humans as sub processes

1<sup>st</sup> Flavor: logical positivism

2<sup>nd</sup> Flavor: compute program with features related to self representation and circular references similar to that of a person

3<sup>rd</sup> Flavor: information structure that can be perceived by some real human to also be a person (Turing Test)



Meta knowledge becomes authority

Collective is good at parameters, bad at user experience

World can be understood by computational processes with humans as sub processes

Relies on Logical Positivism: a sentence or other fragment that can be put into a computer file will mean something in a freestanding way that does not require invoking the subjectivity of a human reader.

EG: a computer can figure out the “meaning” of a sentence if the instructions are correct and comprehensive

# Logical Positivism

To have meaning, a given statement had to be connected to either empirical data or analytic truth.



Only something empirically verifiable logically or empirically is meaningful. Facts trump all else.

Later thinkers distinguished between two classifications of verifiability: "strong" and "weak" verification, the former being something that is conclusively established by experience, the latter only being rendered probable by experience.

# Collective All Wise

Meta knowledge becomes authority

Collective is good at parameters, bad at user experience



Lanier often refers to the “hive mind” with regard to online information  
Those consolidation of bits becomes information (e.g. Wikipedia over true authority sites because edited by the collective)

# Solutionism

Every problem has a definite and computable solution  
(borrowed from architecture and urban planning)

False notion that Internet is a coherent and stable  
influence in our lives

Sometimes right algorithms can lead to wrong  
answers

Grasping easy digital solutions often ignores complex  
causes behind

Questions Silicon Valley assumption that quantifiable  
self is the truer self



Morozov often referenced as an intellectual “hit man.” He wants us to:

- Resist oversimplification of techno-optimism and techno-pessimism to assess each case of technology intervention on its own merits
- Not to fixate on what technology can do without inquiring if it is worth doing (what problem are they solving)
- Do not lose sight of the benefits of subjectivity
- Promote new way of thinking that is technologically literate” – attentive to details, mindful of legal and economic circumstances, historically informed to question appropriateness in each and every situation

Quantification of the self is a crime – it forecloses possibilities and narrows vision (numbers replace other possible interpretations: “quantitative and linear casual explanations that have little respect for the complexities of the actual human world”)

Quantifiable information is the low hanging fruit

Quantifiable Self Movement: “fundamental assumption is that numbers can reveal a core and stable self if only we get the technology right.”

**“Recasting all complex social situations either as neat problems with definite, computable solutions or as transparent and self-evident processes that can be easily optimized—if only the right algorithms are in place!—this quest is likely to have unexpected consequences that could eventually cause more damage than the problems they seek to address.”**

# Solutionism

Sometimes right algorithms can lead to wrong answers

Grasping easy digital solutions often ignores complex causes behind

Silicon Valley assumption is of a quantifiable self that is the truer self



## Solutionism

Presented in To Save Everything Click: Evgeny Morozov

Solutionism: there is an app for everything  
Morozov sees the dot com elite as rewriting the code of social contract largely without public awareness let alone consent

“recasts all of the complex social situations either as neat problems with definite, computable solutions or as transparent and self-evident processes that can be easily optimized if only the right algorithms are in place.”

# Key Takeaways

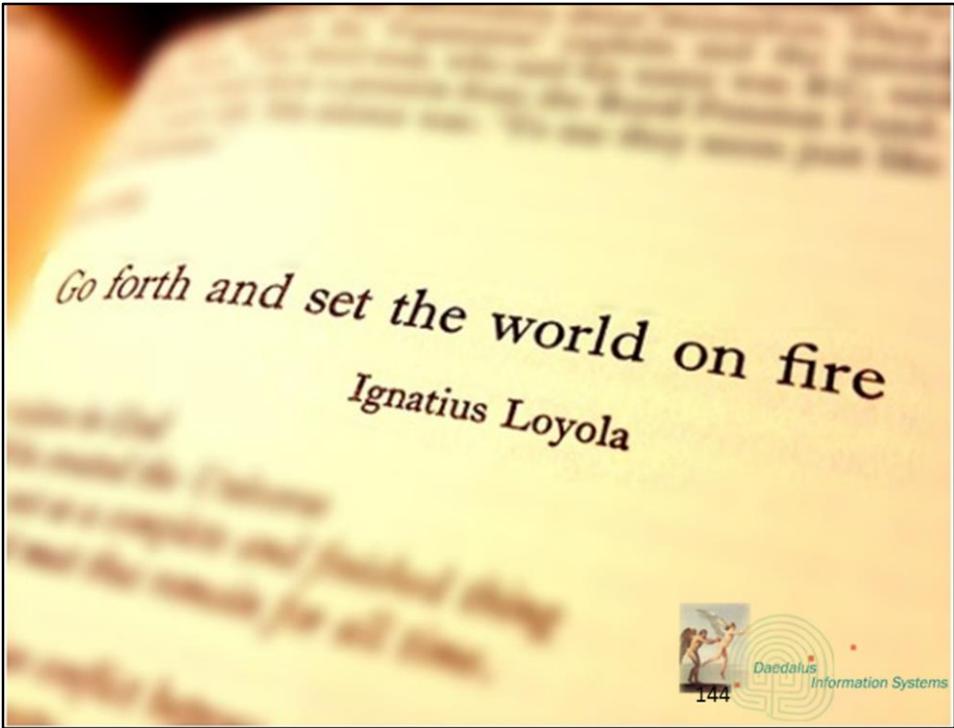
Broaden scope of awareness

Understand the landscape and influences

Embrace new tools and methodologies

We are the representatives of the qualitative self that is truer than the quantitative self represented by AI





# Thank You

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