

*INF4820: Algorithms for
Artificial Intelligence and
Natural Language Processing*

Introduction and Overview

Stephan Oepen & Murhaf Fares

Language Technology Group (LTG)

August 25, 2016

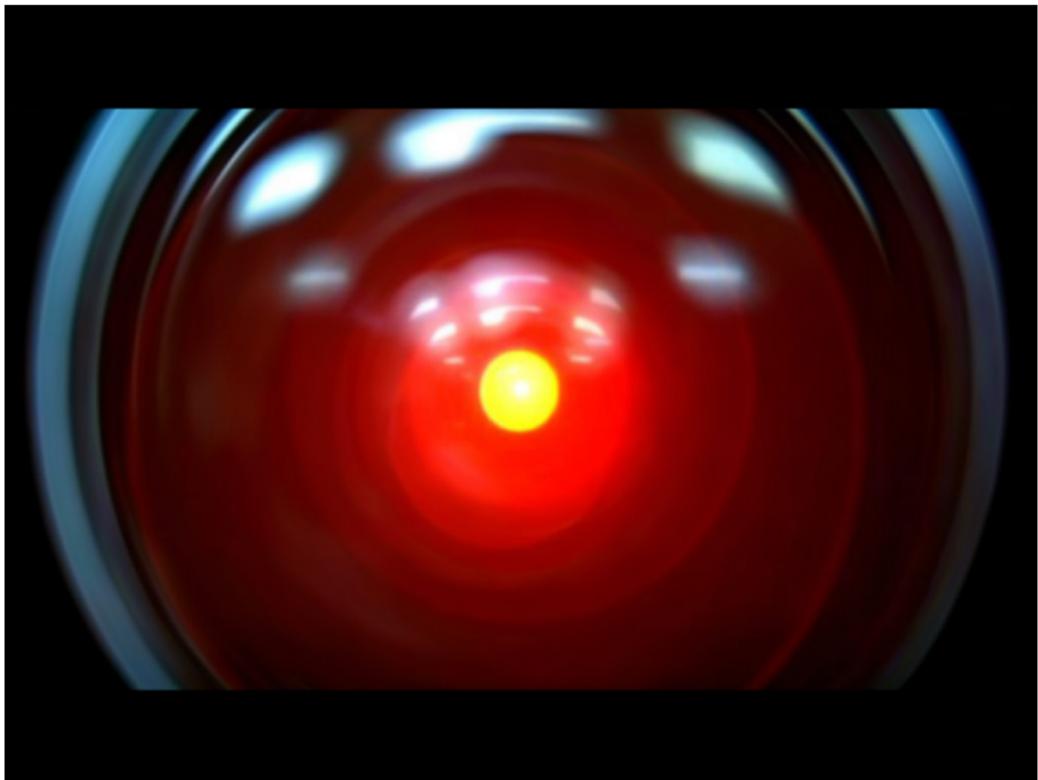




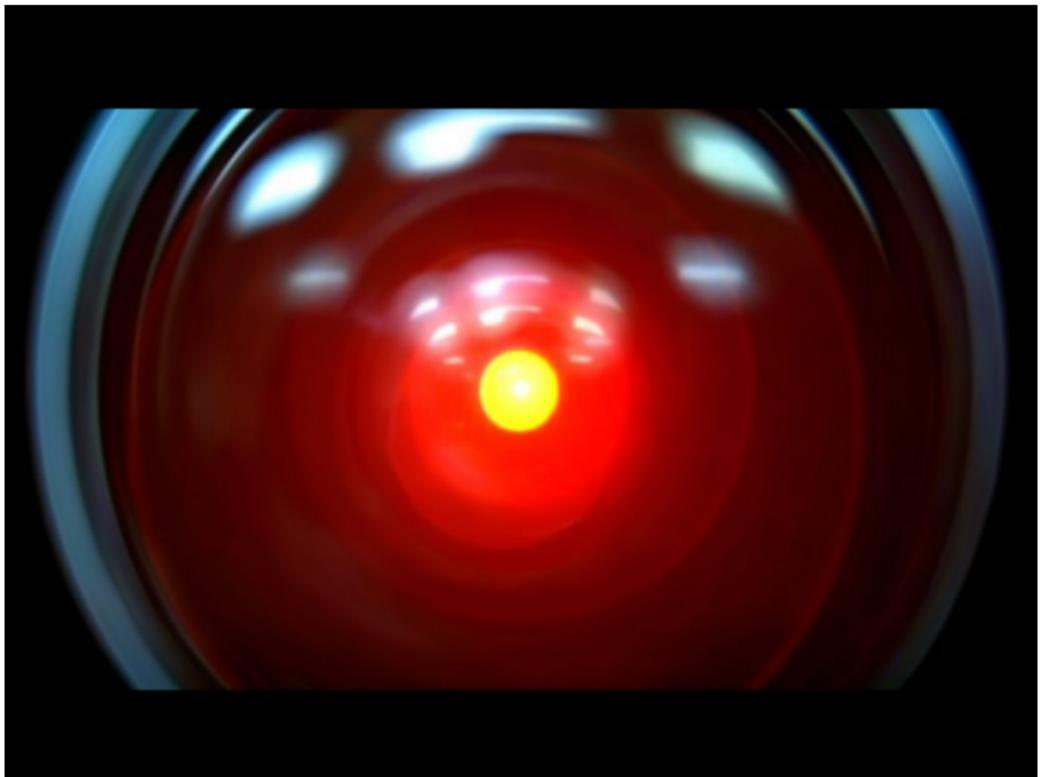
Overview

- ▶ Course motivation and introduction:
- ▶ AI, NLP, ML — What are they?
- ▶ Common Lisp — What and why?
- ▶ Outline of lectures and learning goals.
- ▶ Practical details.

What is AI?



What is AI?



(HAL 9000 in *2001: A Space Odyssey*; 1968)

AI, Hype Cycles, and the End of the World



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- ▶ Stephen Hawking et al. in an op-ed in the Independent (spring 2014):
 - ▶ *it's tempting to dismiss the notion of highly intelligent machines as mere science fiction. But this would be a mistake, and potentially our worst mistake in history.*
 - ▶ *Whereas the short-term impact of AI depends on who controls it, the long-term impact depends on whether it can be controlled at all.*

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- ▶ **Elon Musk** (Tesla Motors, SpaceX) at a MIT talk (fall 2014):
 - ▶ *With AI we are summoning the demon.*

The Future of Life Institute



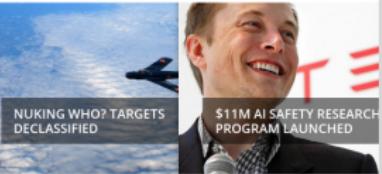
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JULY 6, 2016 The Evolution of AI: Can Morality be Programmed?
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FLI PROJECTS & UPDATES


Hawking Says 'Don't Bank on the Bomb' and Cambridge Votes to Divest \$ 1Billion From Nuclear Weapons


AI Cafes Workshop Highlights

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AI Cafeteria Workshops Highlights

(Spring 2015: Alarm by Hawking, Musk, Norvig, Russel, Wozniak, etc.)

AI in Our Daily Lives (1 of 3)



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https://www.theguardian.com/technology/2016/jun/30/tesla-autopilot-death-self-driving-car-elon-musk

Tesla

Tesla driver dies in first fatal crash while using autopilot mode

The autopilot sensors on the Model S failed to distinguish a white tractor-trailer crossing the highway against a bright sky

Danny Yadron and Dan Tynan in San Francisco

Friday 1 July 2016 00.14 BST

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 Joshua Brown, the first person to die in a self-driving car accident. Photograph: Facebook.

The first known death caused by a self-driving car was disclosed by Tesla Motors on Thursday, a development that is sure to cause consumers to second-guess the trust they put in the booming autonomous vehicle industry.

The 7 May accident occurred in Williston, Florida, after the driver, Joshua Brown, 40, of Ohio put his Model S into Tesla's autopilot mode, which is able to control the car during highway driving.

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(July 2016: A Tesla driver dies while auto-pilot was in control)

AI in Our Daily Lives (2 of 3)



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Technology

Robot security guard knocks over toddler at shopping centre

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The 136kg robot is designed to patrol outdoor areas and secure them from thieves
CREDIT: KNIGHTSCOPE

The Telegraph

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1 iPhone 6 phones infected with 'Touch Disease' that makes screens useless
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2 US attacks power grab by Brussels over Apple tax probe
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2 WikiLeaks exposing data of sick children and abusers

AI in Our Daily Lives (2 of 3)



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(July 2016: Minor injuries from run-in with security robot)

AI in Our Daily Lives (3 of 3)



WIRE | The Rise of Artificial Intelligence and the End of Code

BY CADY METZ 05.15.16

WHAT THE AI BEHIND ALPHAGO CAN TEACH US ABOUT BEING HUMAN



AJA HUANG DIPS his hand into a wooden bowl of polished black stones and, without looking, thumbs one between his middle and index finger. Peering through wire-rim glasses, he places the black stone on

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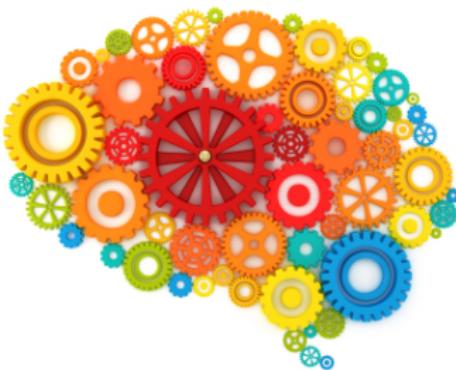
WHAT THE AI BEHIND ALPHAGO CAN TEACH US ABOUT BEING HUMAN

A photograph of Aja Huang, a nine-dan professional Go player, wearing a dark suit and glasses. He is shown from the side, reaching into a wooden bowl to select a black stone for his next move in a game of Go. The background shows a blurred city skyline at night.

AJA HUANG DIPS his hand into a wooden bowl of polished black stones and, without looking, thumbs one between his middle and index finger. Peering through wire-rim glasses, he places the black stone on

(March 2016: Nine-dan professional Go player Lee Sedol loses 4–1)

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- ▶ The term 'AI' coined by John McCarthy (Dartmouth Conference, 1956).
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 - ▶ *The science and engineering of making intelligent machines.*
 - ▶ *Every aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it.*
- ▶ Language always in central place, cf. the Turing Test.

What is AI? (cont'd)



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- ▶ For our purposes: AI is a toolkit of methods for representation and problem solving.



What is Natural Language Processing?

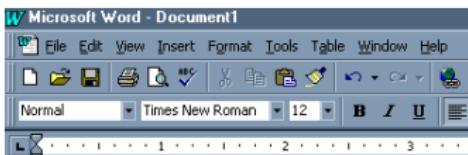


- ▶ Making computers 'understand' human language
- ▶ Aka **language technology** or **computational linguistics**
- ▶ Young and interdisciplinary field:
- ▶ Computer Science + Linguistics
- ▶ (+ Cognitive Science + Statistics + Information Theory + Machine Learning + ...)

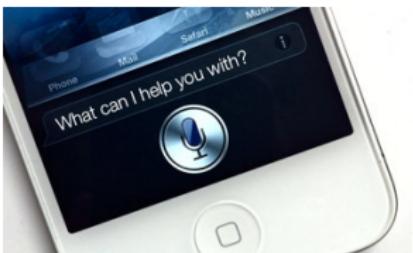
Some Applications



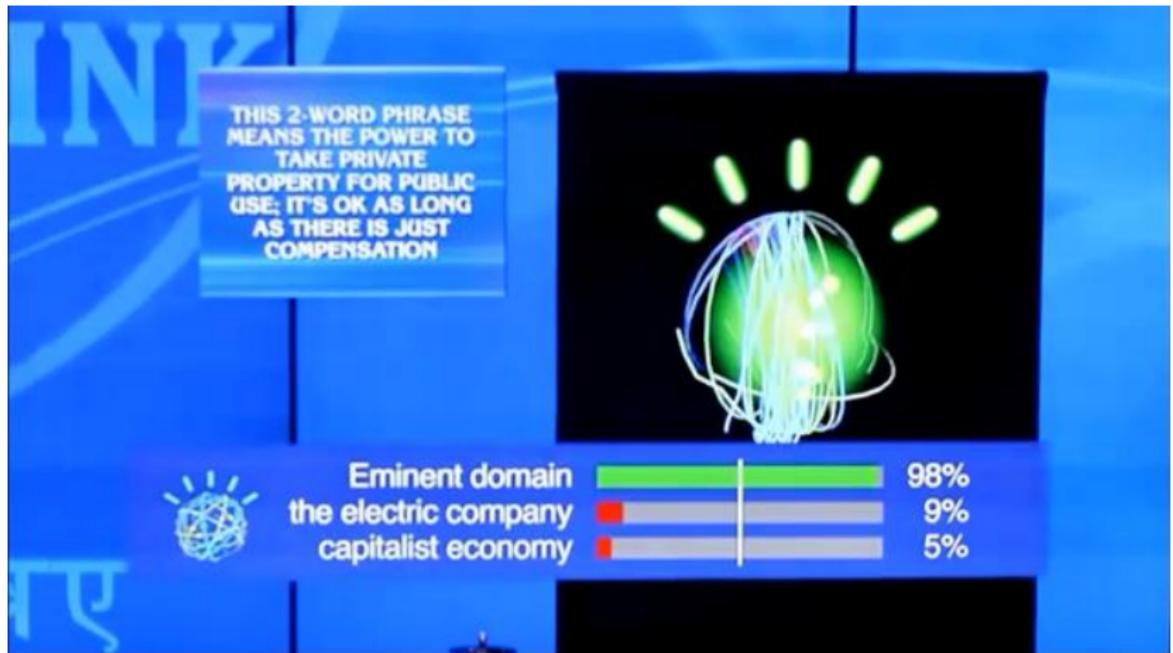
- ▶ Grammar and/or spell checkers, auto-completion
- ▶ Machine translation
- ▶ Q&A systems
- ▶ Dialog systems
- ▶ Speech recognition and synthesis
- ▶ Intelligent information extraction
- ▶ Summarization
- ▶ Sentiment analysis
- ▶ Any application requiring an understanding of language...



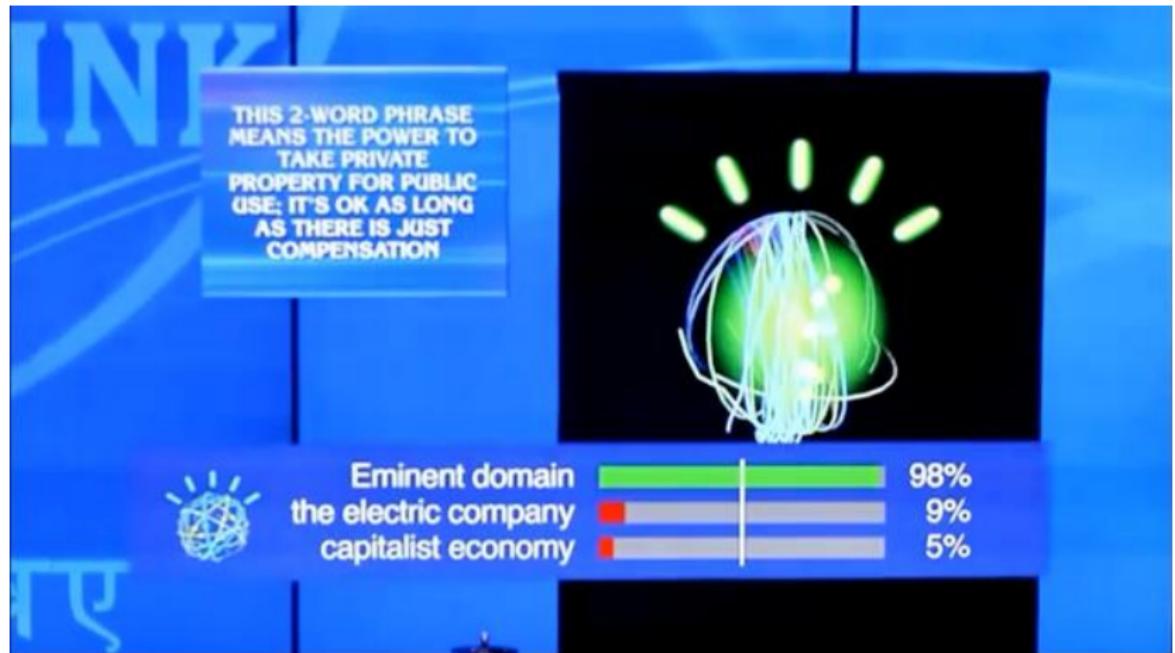
This are what a grammar error looks like in Word



What is AI?



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(IBM Watson beats long-time *Jeopardy!* champions; 2011)



Ambiguity

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- ▶ All levels of linguistic description are associated with ambiguities.

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- ▶ For humans, ambiguity is a feature: language is an **efficient code**.
 - ▶ The same expressions can be re-used in different contexts.
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- ▶ **Disambiguation** is a central problem in NLP → **Search problems**.

Ambiguity: Some examples



Word level ambiguity

- Norwegian: *rett.*

Ambiguity: Some examples



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- ▶ Norwegian: *rett*.
- ▶ English: *meal, dish, straight, correct, fair, justice, right, court, law, direct, grade, ...?*

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De hadde laget en deilig **rett** av grønnsaker.

Streken må være **rett**.

Kunden har alltid **rett**.

Du har **rett** til en advokat.

Det er lovlig i henhold til norsk **rett**.

Slikter skjer **rett** som det er.

Vennligst **rett** disse prøvene!

Vi kjørte **rett** hjem.



Referential Ambiguity

The authorities jailed the protesters because they { *advocated revolution.*
feared revolution.

Ambiguity: Some Examples

Referential Ambiguity

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Sentence-Level Ambiguity

I like eating sushi with { *tuna.*
sticks.

Ambiguity: Some Examples

Referential Ambiguity

*The authorities jailed the protesters because they { advocated revolution.
feared revolution.*

Sentence-Level Ambiguity

*I like eating sushi with { tuna.
sticks.*

Acoustic Ambiguity

*Let's talk about how to { recognize speech
wreck a nice beach*



- ▶ Traditionally; two broad paradigms in NLP (and AI).
 - ▶ The **rationalist** approach, based on hand-crafted formal rules and manually encoded knowledge.
 - ▶ The **empiricist** approach, based on automatically inferring statistical patterns from data.



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- ▶ Late 1980s: Empirical systems outperform rule-based in the area of speech recognition.
- ▶ 1990s: NLP as whole sees a shift of interest from rationalist towards empirical approaches.
- ▶ 2000s: No longer conceived as opposing poles, but **complementary** approaches typically used together.

- The theoretical foundations are studied within the field of **machine learning** (ML) or **statistical learning theory**.

Machine Learning

... *the study of computer algorithms that improve automatically through experience* (Tom Mitchell 1997).

- Goal: Learn from examples, to make predictions about new data.

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Machine Learning

... *the study of computer algorithms that improve automatically through experience* (Tom Mitchell 1997).

- Goal: Learn from examples, to make predictions about new data.
- Has applications in many other **data-intensive** sciences besides NLP, e.g. meteorology, biology, physics, robotics, signal processing, etc.
- An arsenal of methods: decision trees, support vector machines, maximum entropy models, naïve Bayes classifiers, artificial neural networks, genetic algorithms, ...

Lisp



- ▶ Powerful high-level language with long traditions.
- ▶ Especially strong support for **symbolic** and **functional** programming.
- ▶ “Discovered” by **John McCarthy** in **1958**.



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 - ▶ Then one of his students, Steve Russell, implemented an interpreter for the formalism, and Lisp the programming language was born.



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- ▶ “Discovered” by **John McCarthy** in **1958**.
 - ▶ Initially intended as a mathematical formalism.
 - ▶ Then one of his students, Steve Russell, implemented an interpreter for the formalism, and Lisp the programming language was born.
- ▶ Rather than Lisp becoming outdated, the tendency has been that other languages have developed towards Lisp.





```
(print "Hello world!")
```

- ▶ Several dialects; we will be using Common Lisp.
- ▶ Fully ANSI-standardized and stable.
- ▶ Rich language: multitude of built-in data types and operations.
- ▶ Easy to learn:
 - ▶ extremely simple syntax;
 - ▶ straightforward semantics.

An Experiment in Live Programming



The Factorial Function

$$n! \equiv \begin{cases} 1 & \text{for } n = 0 \\ n \times (n - 1)! & \text{for } n > 0 \end{cases}$$

An Experiment in Live Programming



The Factorial Function

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Common Lisp Implementation

```
(defun ! (n)
  (if (= n 0)
      1
      (* n (! (- n 1))))))
```

A Note on Lisp and AI



- ▶ Often hailed (or dismissed) as “**the AI language**”.
- ▶ While not quite true, there are several reasons for this coupling:
- ▶ AI coined by **McCarthy** in the mid-1950s.
- ▶ Lisp conceived by **McCarthy** in the mid-1950s.



A Note on Lisp and AI



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- ▶ AI coined by **McCarthy** in the mid-1950s.
- ▶ Lisp conceived by **McCarthy** in the mid-1950s.
- ▶ In addition to being fast and powerful,
Lisp is particularly well suited for:
 - ▶ Explorative programming
 - ▶ Rapid prototyping
 - ▶ Incremental and interactive development
 - ▶ Extending the language itself



Lisp + Emacs = Good Match



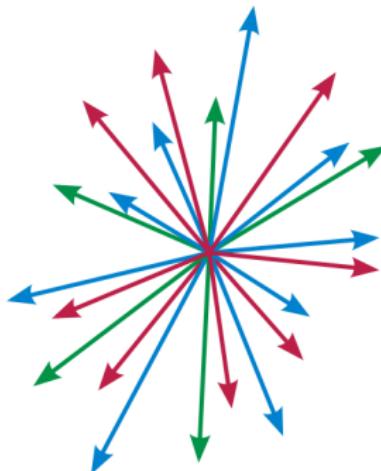
- ▶ Steep learning curve, but with a big pay-off:
- ▶ Emacs is an unusually powerful editor.
- ▶ Written in Emacs Lisp.
- ▶ Highly customizable—the Emacs Lisp dialect is also used as an extension language.
- ▶ Different “modes” make Emacs sensitive to different editing needs, e.g. depending on the specific programming language used.
- ▶ Prerequisite for an enjoyable Emacs experience: Spend some time mastering basic key commands!



Overview of Lectures



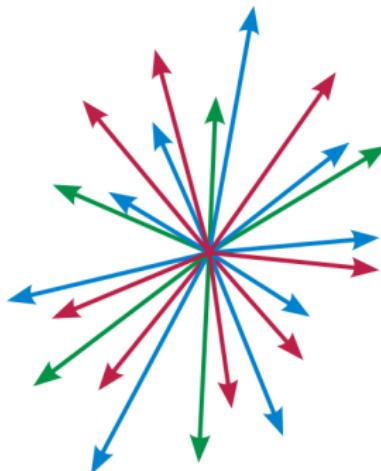
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- ▶ **Recurring themes:** Machine learning, scalable data representations, search, dynamic programming.



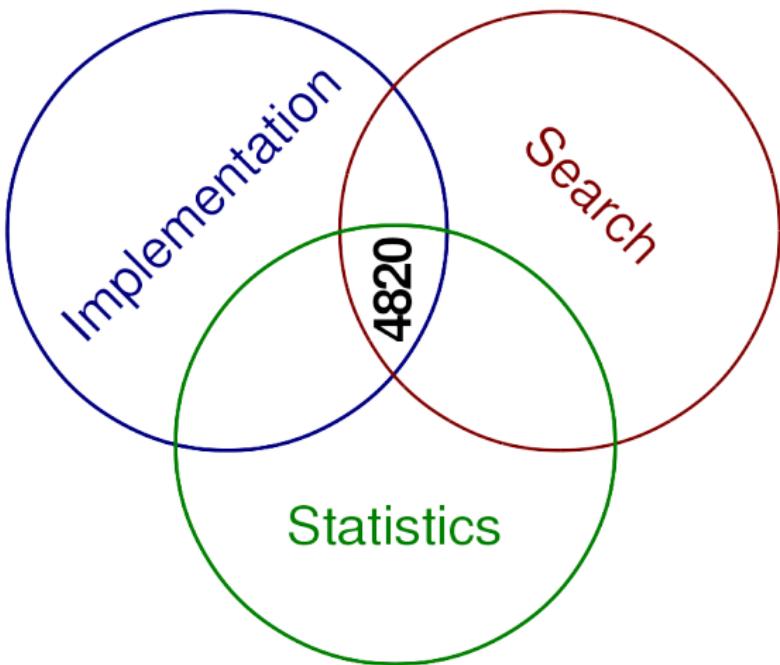
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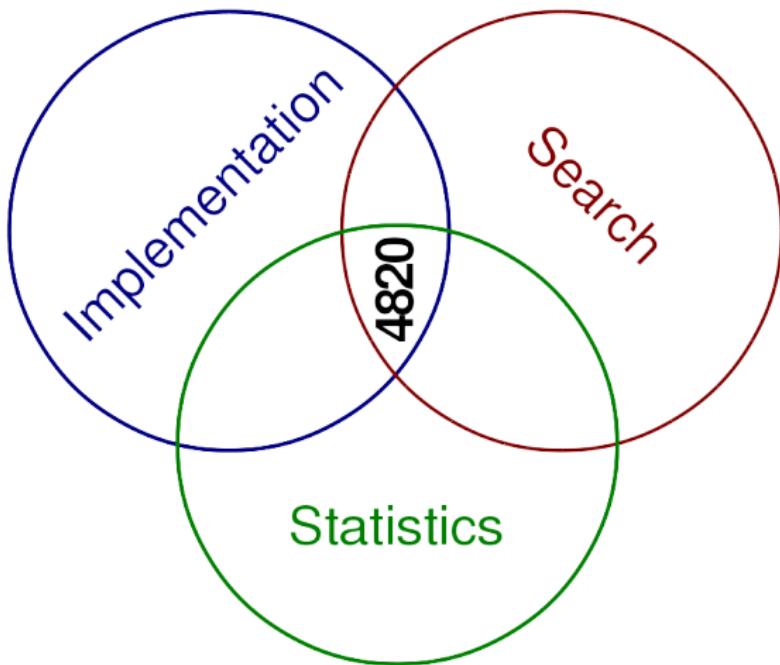
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- ▶ **Recurring themes:** Machine learning, scalable data representations, search, dynamic programming.
- ▶ Two hours of lectures every week; two-hour laboratory **weekly**



Very High-Level Course Summary



Very High-Level Course Summary



Efficient and Scalable Algorithms and Data Structures for
Searching (Probabilistically) Weighted Solution Spaces

Obligatory Exercises



- ▶ Three **obligatory exercises**:
- ▶ Exercise (2) and (3) have two **parts** each;
- ▶ Five **problem sets** in total.
- ▶ In order to pass and qualify for the exam you need at least
 - ▶ 6 of 10 possible points for Exercise (1),
 - ▶ 12 of 20 possible points for (2a) + (2b),
 - ▶ 12 of 20 possible points for (3a) + (3b).
- ▶ Extensions can only be given in case of illness, and re-submissions will not be possible.
- ▶ See course page for the schedule (tba).

Infrequent Experiments in High-Tech Teaching



- ▶ For student involvement and **incremental exam preparation**:
- ▶ occassional short quiz sessions → **extra points** towards exercises.



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Example Quiz (0 + 0 Points)

1. Live programming can be useful?

A: yes; B: no



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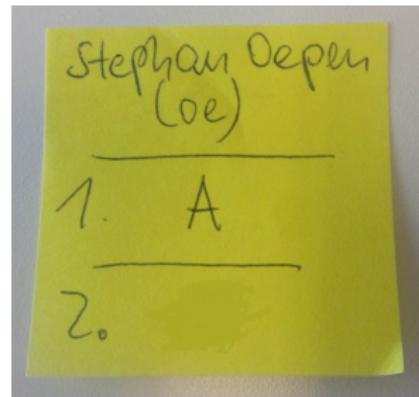
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A: Alan Turing; B: John McCarthy

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Introduction to Information Retrieval (Available On-Line)

Other recommended resources:

- ▶ Despite being 20 years old and long out-of-print *On Lisp* by Paul Graham is still a great read.
 - ▶ Freely available on-line: <http://www.paulgraham.com/onlisp.html>
- ▶ The Common Lisp ‘HyperSpec’:
 - ▶ <http://www.lispworks.com/documentation/HyperSpec/Front/>



► Questions?

- Piazza: on-line discussion board linked from course page.
- inf4820-help@ifi.uio.no reaches all course staff:
- Murhaf Fares;
- Stephan Oepen;



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- Stephan Oepen;
- Elena Volkova (laboratory assistant);
- {murhaff | oe | elenavo}@ifi.uio.no.

► Messages:

- Check your [UiO email](#) regularly;
- Subscribe to the RSS feed of the course page;
- Participate in the on-line discussion board.