IN[34]120 - Søketeknologi 🖥️📚🔍

2024-11-05 🇺🇸🦅 (det er valg i dag 🙀🙀🙀)

Tema: Websøk m/venner 🫀🍗
Basert på 2023-slides

- Administravia
- PageRrank
- Bloom filters
- Cuckoo filters
- Live-progge D-1?
- Oblighjelp

ti. 5. nov.	14:15–16:00	Websøk m/venner.	OJD, Datastue Chill	O. R. Jahren	PageRank, Bloom filters, cuckoo filters. LF D-1. Siste gruppetime før deadline for oblig E.
ti. 12. nov.	14:15–16:00	Repetisjon.	OJD, Datastue Chill	O. R. Jahren	SVMer? Compression? ANN?
ti. 19. nov.	14:15–16:00	Eksamensforberedelser.	OJD, Datastue Chill	O. R. Jahren	Regner med vi løser gamle eksamensoppgaver i fellesskap.

Her er vi

IN4120: Science fair deadlines

- ✔Group self-assignment: 2024-10-21
- ✔Topic selection: 2024-11-04
- Contact prof. Øhrn about this 🦅
- Selve dagen: 2024-11-18.

Assignment D

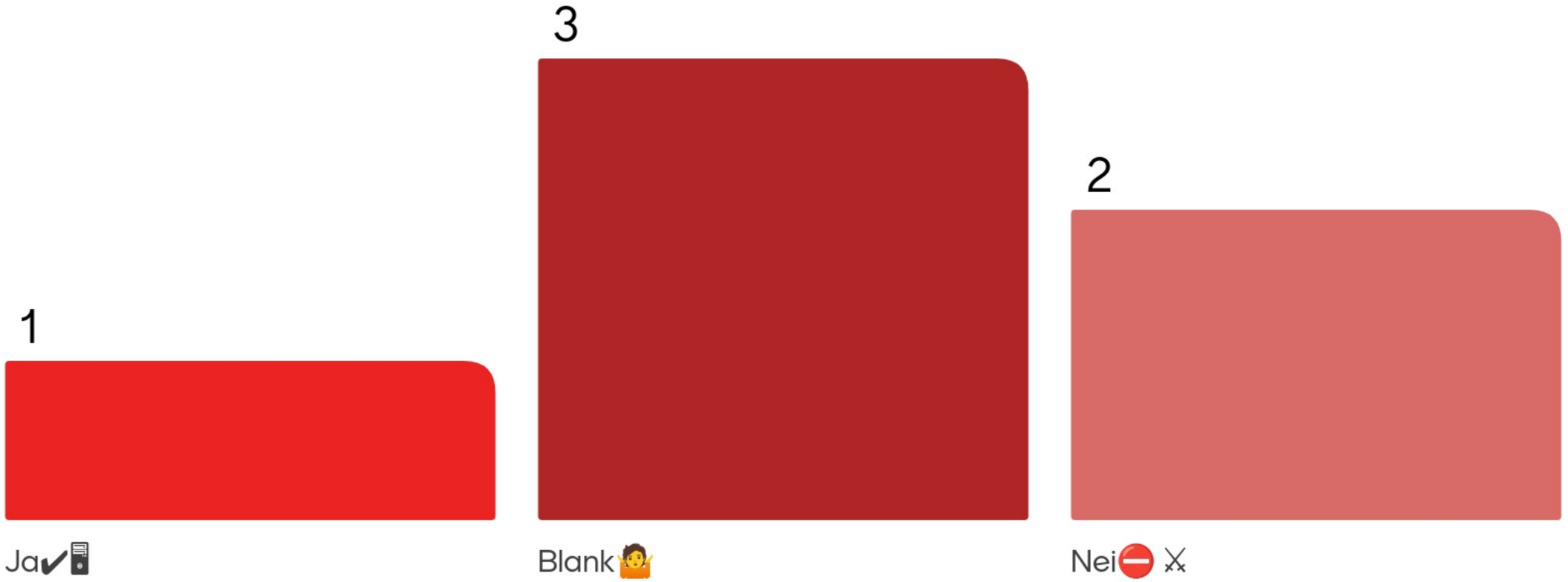
- Frist forrige fredag ☀️
- Alle ferdig rettet
- Alle som leverte fikk godkjent 👏👏

Assignment D: Løsningsforlsag ute

- → Kom i går kveld😎👍
- → Ligger på Github (kan pulles)
- → Ingen avhengigheter (?)

NB: Har ikke gjort vector-delen før

Live-progge D-1 etterpå?



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Assignment E

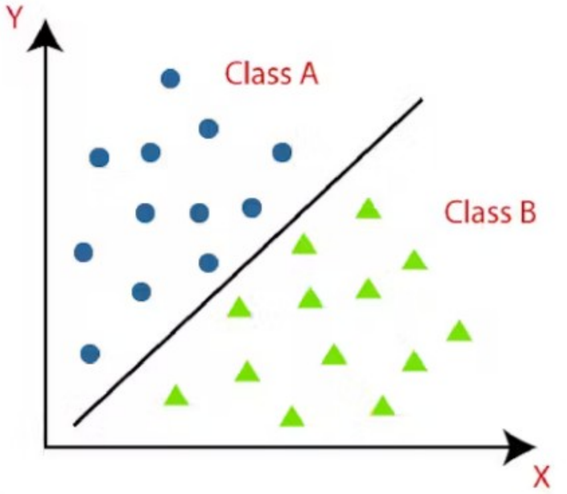
- Frist på fredag 👮
- Siste oblig 🙀

Slides om Naïve Bayes

Fra 2023. Ligger her som referanse.

ASSIGNMENT HINTS! FOR E-1

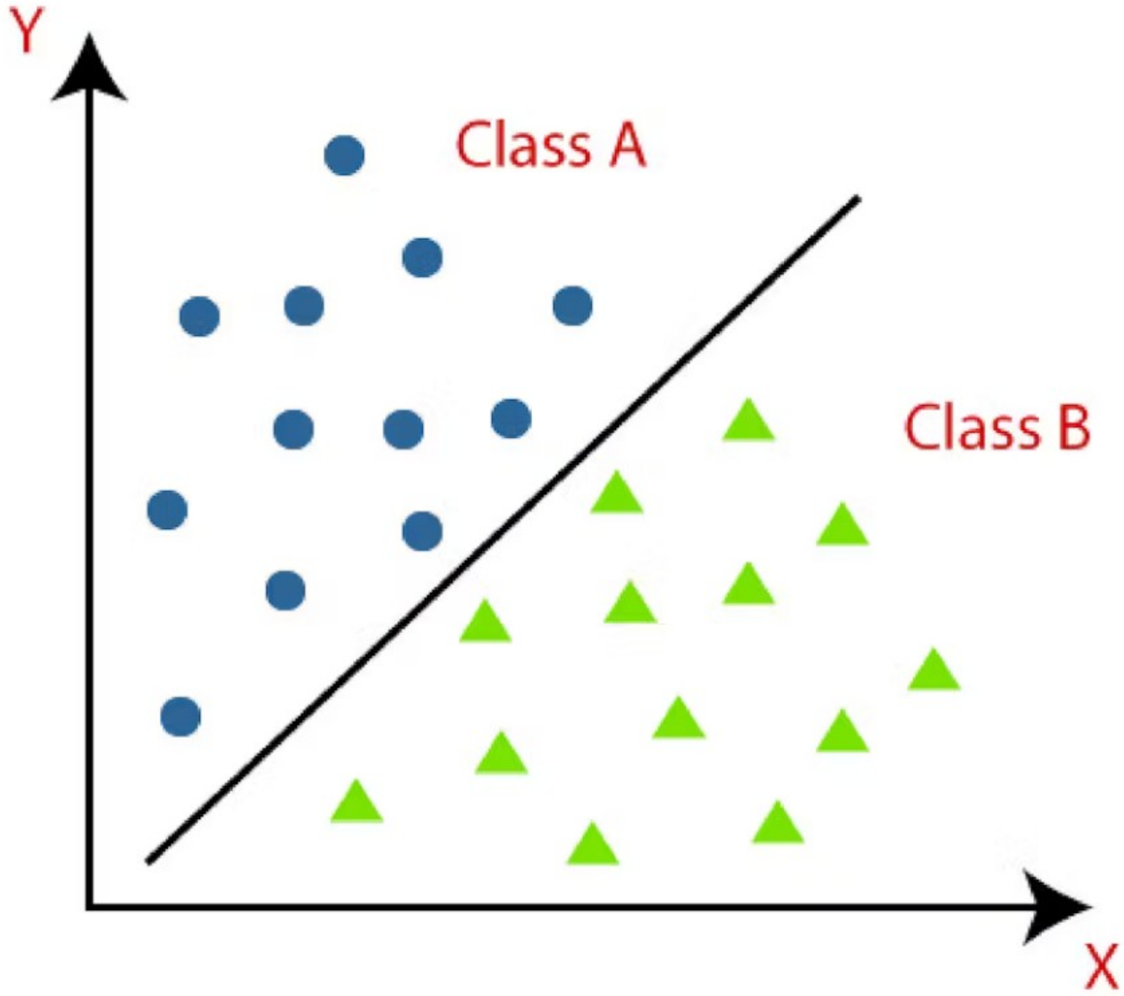
- Naïve Bayes classification
  - What is classification?
    - Determine what language a text is*
  - We have classes
    - Our classes are the languages.
      - In E-1: NO, EN, DA, GER
      - *How could we "learn" more categories? What determines what classes we can use?*
  - Test what class fits the best
    - Try all classes. Best result is our prediction.
    - Report the findings



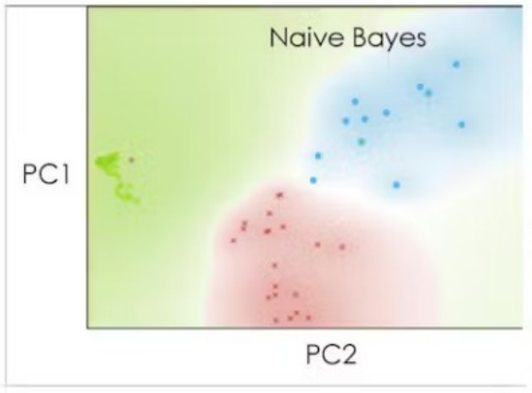
*Oversimplification. Other forms of classification exist also. They are not relevant for E-1.

CLASSIFICATION

- "Given an input, what class does it belong to?"
  - "*Ég kann ekki ríta íslensku*" -> what language is this?
    - The language is our class or category
- In this context, "class" and "category" mean the same
- Machine learning / AI
  - Naïve Bayes
  - Support Vector Machines (SVMs)
  - Supervised / unsupervised learning
    - Relates to how the models are trained
    - Supervised learning
      - We have labeld training data
    - Unsupervised learning
      - Unlabelled data
      - The model must find the categories by itself



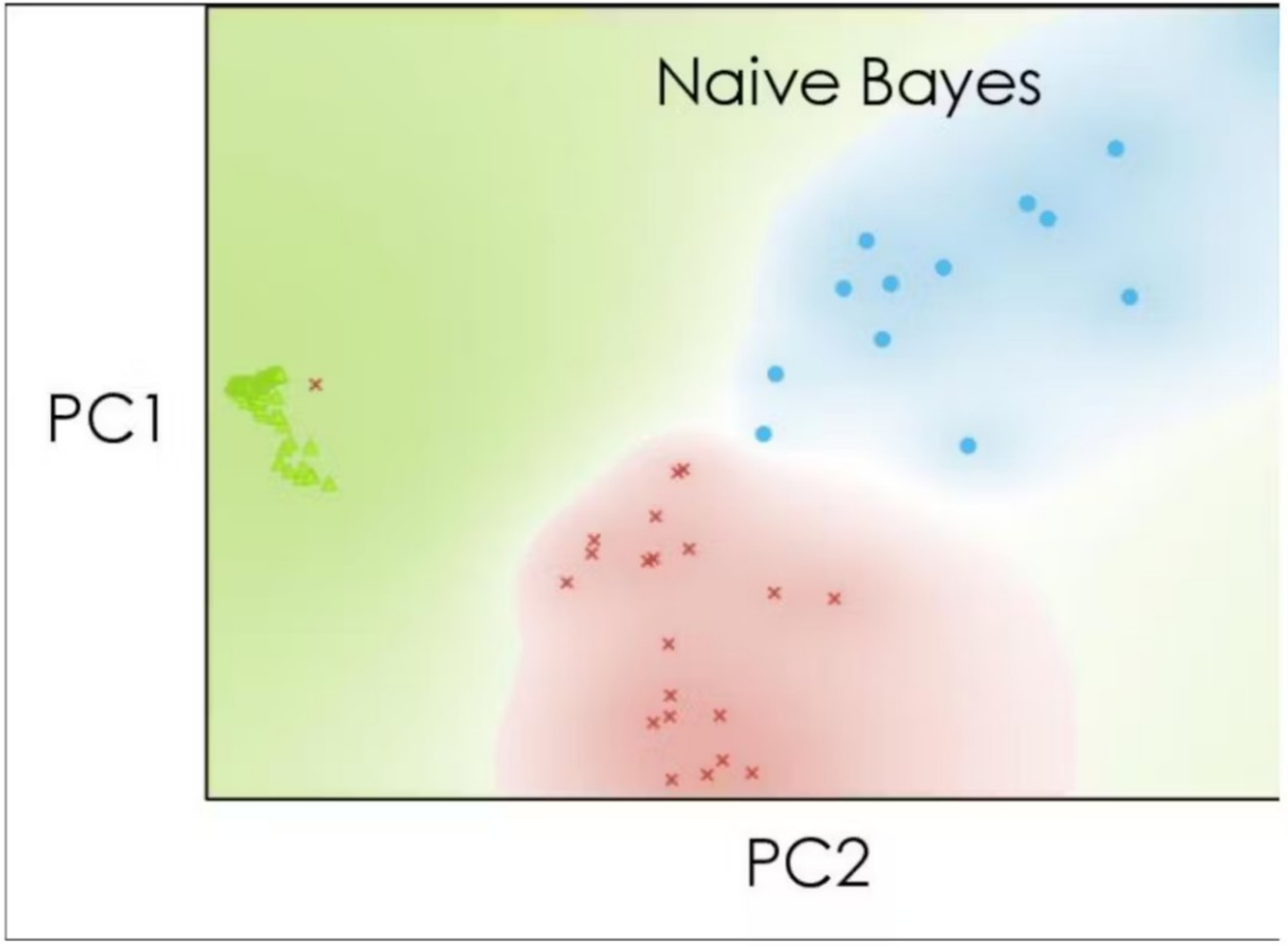
NAÏVE BAYES



- Why naïve?
  - Uses Bag-of-words model
    - I.e. the order of the tokens doesn't matter
- Why Bayes?
  - Named after Thomas Bayes (1701-1761), English statistician

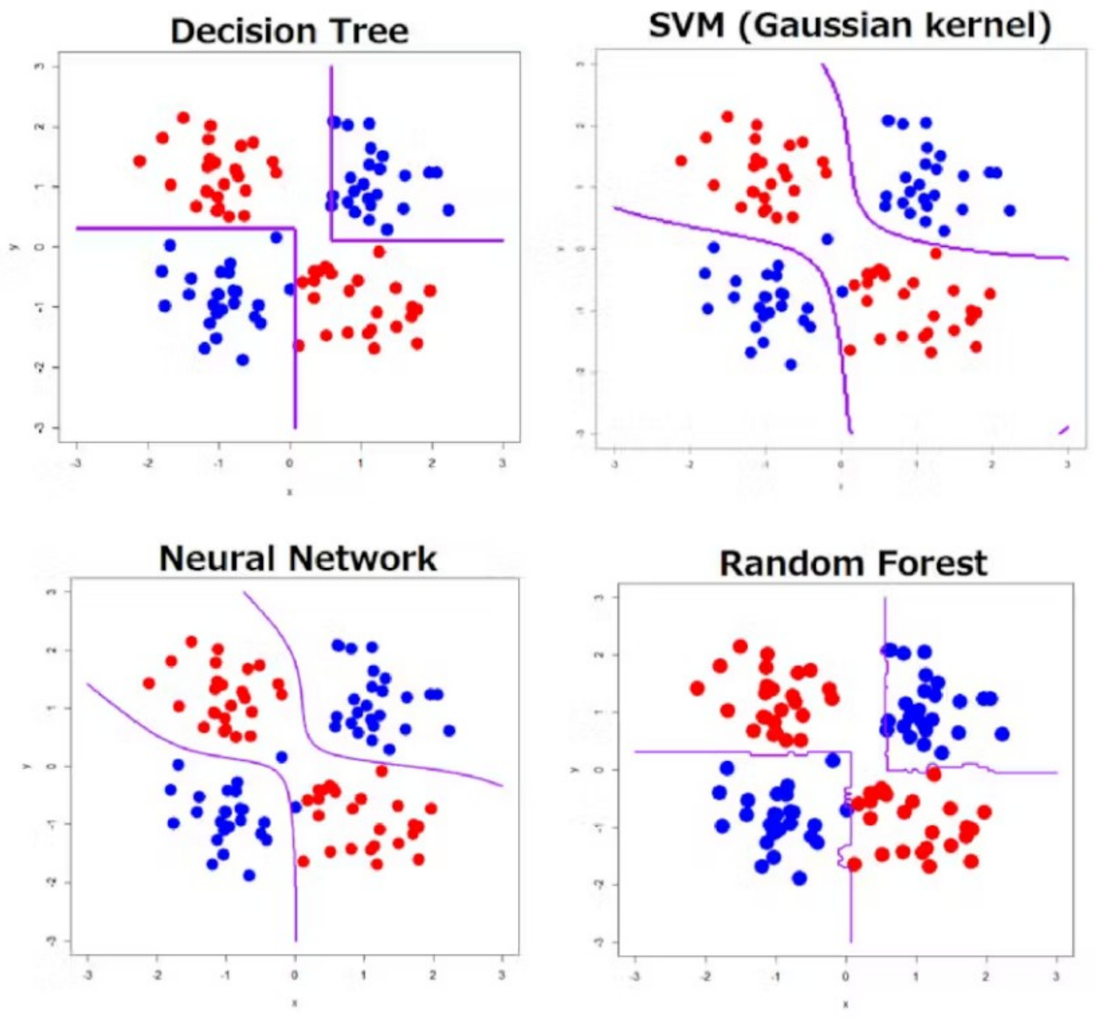
DECISION BOUNDARIES

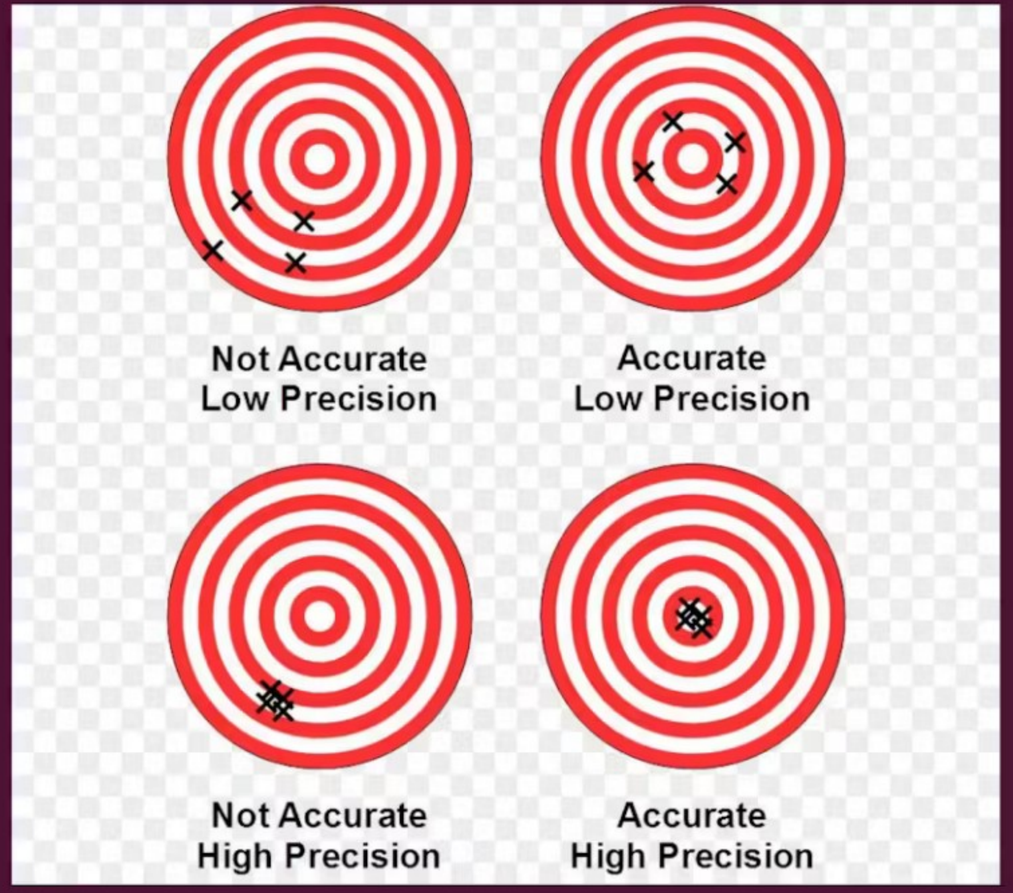
- Note how the color blobs for the most part match our samples
  - The marks are our samples
- But there are some outliers
  - **Note the red cross in the sea of green**
  - This means that our model would probably make some mistakes sometimes
- Naïve Bayes is very basic, other methods can achieve better results



THE IMPACT OF DECISION BOUNDRIES

- Looking at the decision boundries allows us to visually evaluate the effectiveness of our model
- Further reading: see "overfitting" and other models in other språktek-courses like IN2110, IN3050/4050 and IN4080





CLASSIFICATION METRICS

- Accuracy
  - How many predictions are correct?
- Precision
  - Are we confident in our
- Recall
  - Did we find what we should have found?

CODE FOR ASSIGNMENT E-1!

- self.__compute_priors(training_set)
- self.__compute_vocabulary(training_set, fields)
- self.__compute_posteriors(training_set, fields)
- self.__classify(self, buffer: str)

PRIORS! (LONG FORM: 'PRIOR PROBABILITY')

```
42
43      def __compute_priors(self, training_set):
44          """
45          Estimates all prior probabilities needed for the naive Bayes classifier.
46          """
47          raise NotImplementedError("You need to implement this as part of the assignment.")
```

- What is a prior?
  - The probability of seeing a class regardless of the term
  - Intuition: if 85% of the animals in your farm are pigs, if you select a random animal it will probably be a pig.
- How can it be calculated?
  - You need the counts of the categories
    - How big are the categories
    - How many terms do you have with all categories added up
  - Big categories are more probable

VOCABULARY!

```
49      def __compute_vocabulary(self, training_set, fields):
50          """
51          Builds up the overall vocabulary as seen in the training set.
52          """
53          raise NotImplementedError("You need to implement this as part of the assignment.")
```

- What terms do we have in our corpora?
  - We need to add all the terms to our vocabulary (self.__vocabulary)
- Iterate over the training set corpora
  - Iterate over the documents in the corpus
    - Iterate over the fields (fields is given as arg)
      - Iterate over the terms in the field
        - Add the terms (self.__vocabulary.add_if_absent(term))

POSTERIORS!

```
55      def __compute_posteriors(self, training_set, fields):
56          """
57          Estimates all conditional probabilities needed for the naive Bayes classifier.
58          """
59          raise NotImplementedError("You need to implement this as part of the assignment.")
```

- "All conditional probabilities"….?
  - We must:
    - Principally: set conditionals
    - But how?
      - Set and use the denominators

POSTERIORS CONT.

1. We must deal with all categories and all corpora. => Iterate over the training set
2. We need all terms for all fields for all documents in the corpus
3. Count the terms of step #2
4. The denominator for the current category will be the sum of the counting from step #3 added with the vocabulary size
    1. This provides a relation between corpus size and probability
5. The conditional for the category will be set for each term in the category: The conditional for term t given class x will be the term frequency of t +1* divided by the denominator for x.
    1. * We use "'laplace-add-one'-smoothing", which entails adding 1.

CLASSIFY

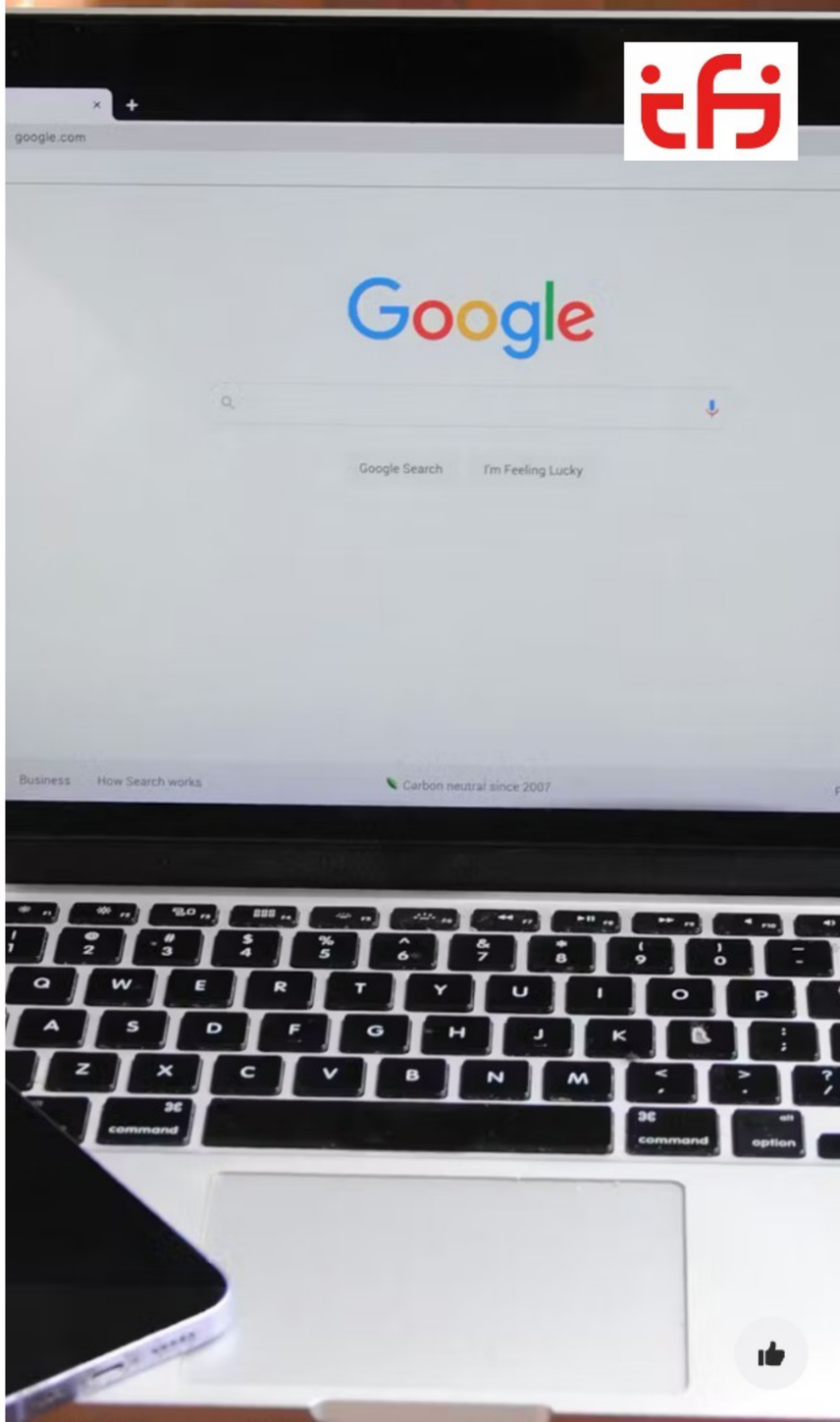
```
69      def classify(self, buffer: str) -> Iterator[Dict[str, Any]]:
70          """
71          Classifies the given buffer according to the multinomial naive Bayes rule. The computed (score, category) pairs
72          are emitted back to the client via the supplied callback sorted according to the scores. The reported scores
73          are log-probabilities, to minimize numerical underflow issues. Logarithms are base e.
74
75          The results yielded back to the client are dictionaries having the keys "score" (float) and
76          "category" (str).
77          """
78          raise NotImplementedError("You need to implement this as part of the assignment.")
```

- We have all the probabilities from
- Given a text (“buffer”), classify it.
  - Find the terms
  - Init a hashmap of scores. Each category starts with its prior.
  - Iterate over the categories. Increase the score by the conditional for every term given the category.
    - Use 1/denominator for the cases when the term t never appears in the category (0 is a bad value)
  - Finally yield all values for all categories in sorted order

Websøk 🥩🥔

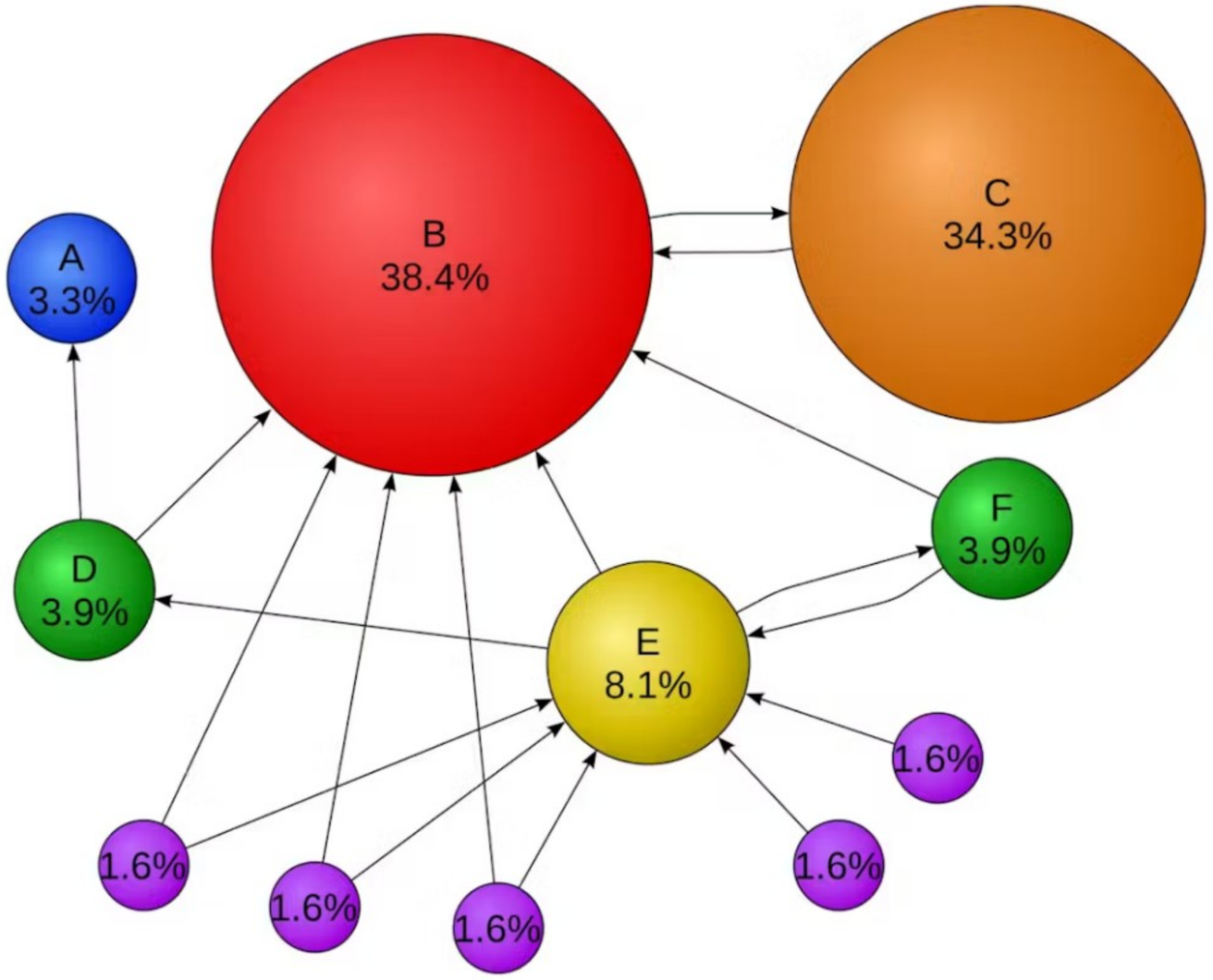
Søketeks kjøtt og poteter?

🥩🥔🥔



WEB SEARCH

- Basic principle: Query -> sorted list of ranked web pages
- The web is a directed graph of sites. Links are edges and pages are nodes.
  - Graphs allow us to use maths, logic and algorithms!



PAGERANK

- Ranking algorithm for web pages
  - Invented by and named for Larry Page, Google co-founder. Photo on the left.
    - Ofc also a good pun. *See if you can figure out why.*
  - Main principle:
    - If several sites {a, b, c} are linking to site x, site x is probably a good site and should be ranked highly(? Grammar).
      - (…Obviously?)
      - PageRank is a big deal because of finding a way of caluclating this.

Larry Page

90 languages

Article Talk | Read View source View history Tools

From Wikipedia, the free encyclopedia

For the singer, see Larry Page (singer).

Lawrence Edward Page[2][3][4] (born March 26, 1973) is an American businessperson, computer scientist and internet entrepreneur best known for co-founding Google with Sergey Brin.[2][5]

Page was chief executive officer of Google from 1997 until August 2001 when he stepped down in favor of Eric Schmidt and then again from April 2011 until July 2015 when he became CEO of its newly formed parent organisation Alphabet Inc. which was created to deliver "major advancements" as Google's parent company,[6] a post he held until December 4, 2019 when he along with his co-founder Brin stepped down from all executive positions and day-to-day roles within the company. He remains an Alphabet board member, employee, and controlling shareholder.[7]

As of October 2023, Page has an estimated net worth of $118 billion according to the Bloomberg Billionaires Index, making him the sixth-richest person in the world.[8] He has also invested in flying car startups Kitty Hawk and Opener.[9]

Page is the co-creator and namesake of PageRank, a search ranking algorithm for Google[17] for which he received the Marconi Prize in 2004 along with co-writer Brin.[18]

Early life

Larry Page

Page speaking at the European Parliament in 2009

Born	Lawrence Edward Page March 26, 1973 (age 50)

PAGERANK A BIG DEAL?

GETS GOOD SCREEN REAL ESTATE ON WIKIPEDIA.

(USE THIS INFORMATION AS YOU WANT)

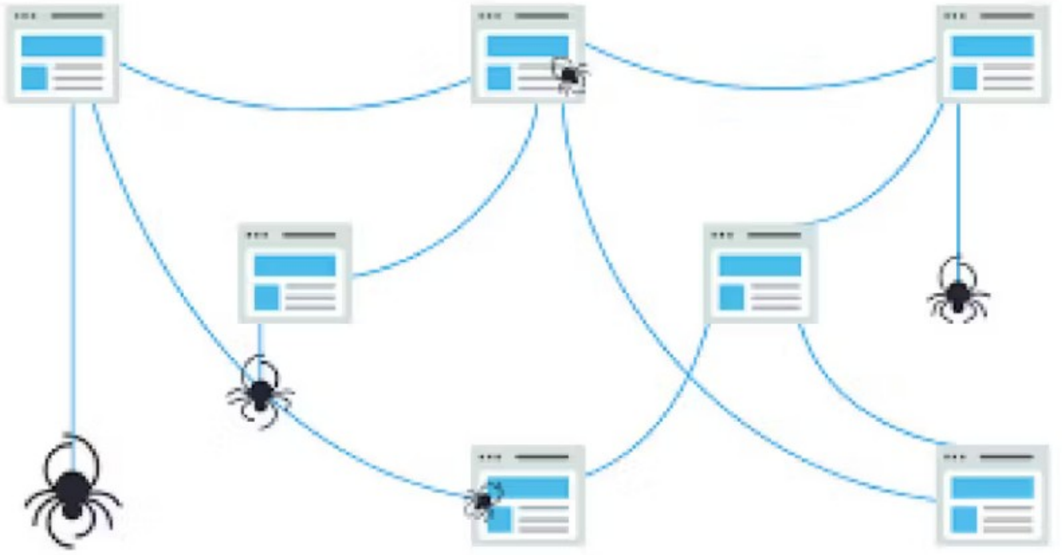
TANGET: THE IMPORTANCE OF ALGORITHMS IN THE SEARCH INDUSTRY

GOOGLE IS AN ADVERTISMENT COMPANY

HAVING A GOOD ALGORITHM IS IRRELEVANT IF YOU CANNOT KEEP AFLOAT FINANCIALLY

CRAWLING

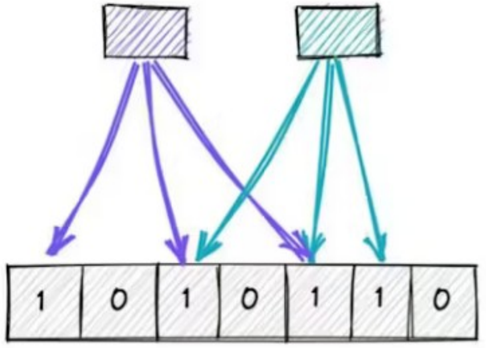
- What is crawling?
  - ”Finding” all the pages on the internet and learning what they contain
- Do you want to crawl?
  - No, You want to avoid it
    - Why?
      - Painful
      - Expensive
      - Possibly illegal



Data structures

Bloom & Cuckoo

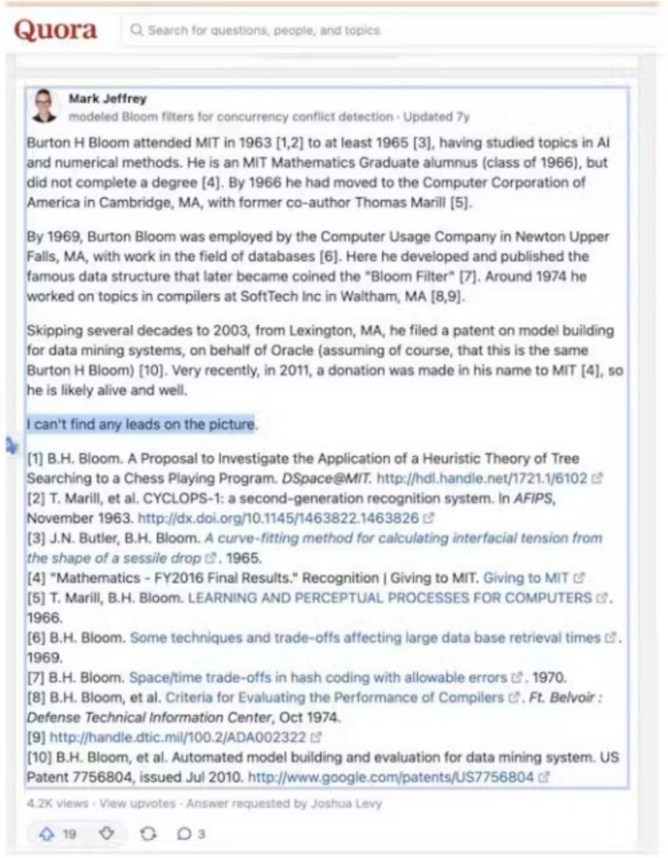
BLOOM FILTERS



- Use case: "Is this element a part of my set?"
  - Main claim to fame: uses minimal memory
- Can give false positives
  - I.e. it can say "yes you have this" without it being true
- But always true negatives
  - I.e. if it says "no, you don't have this", you can be sure of it being correct

- NB: You cannot delete items
  - Cuckoo filters address this. Covered in a few slides.
  - Also: Counting Bloom filters exist. Not so relevant.
  - For understanding, think: *Why is it impossible to delete items?*

BLOOM FILTERS CONT.



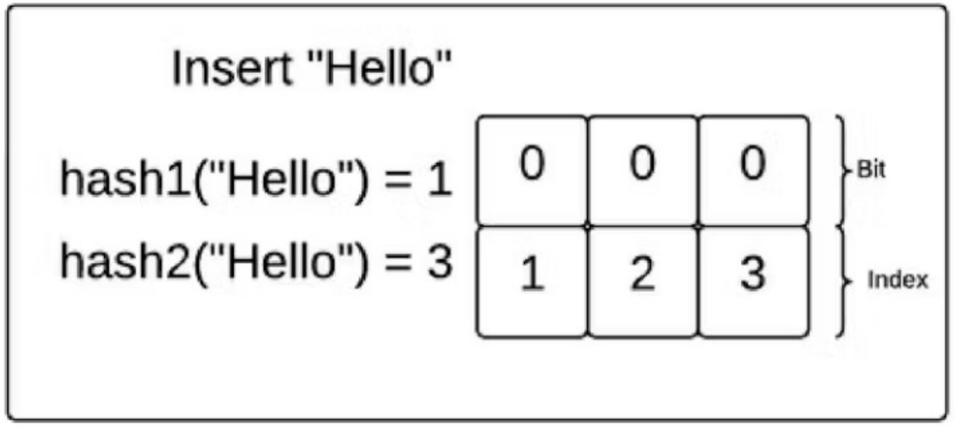
- Why Bloom?
  - Named for Burton Howard Bloom
    - He has no Wikipedia page and no images online.
    - His seminal paper is in the repo.
- Why filter?
  - Not 100% sure. GPT-4 claims it is to filter out unnecessary operations. May be true.

GPT-4

What makes Bloom filters a "filter"?

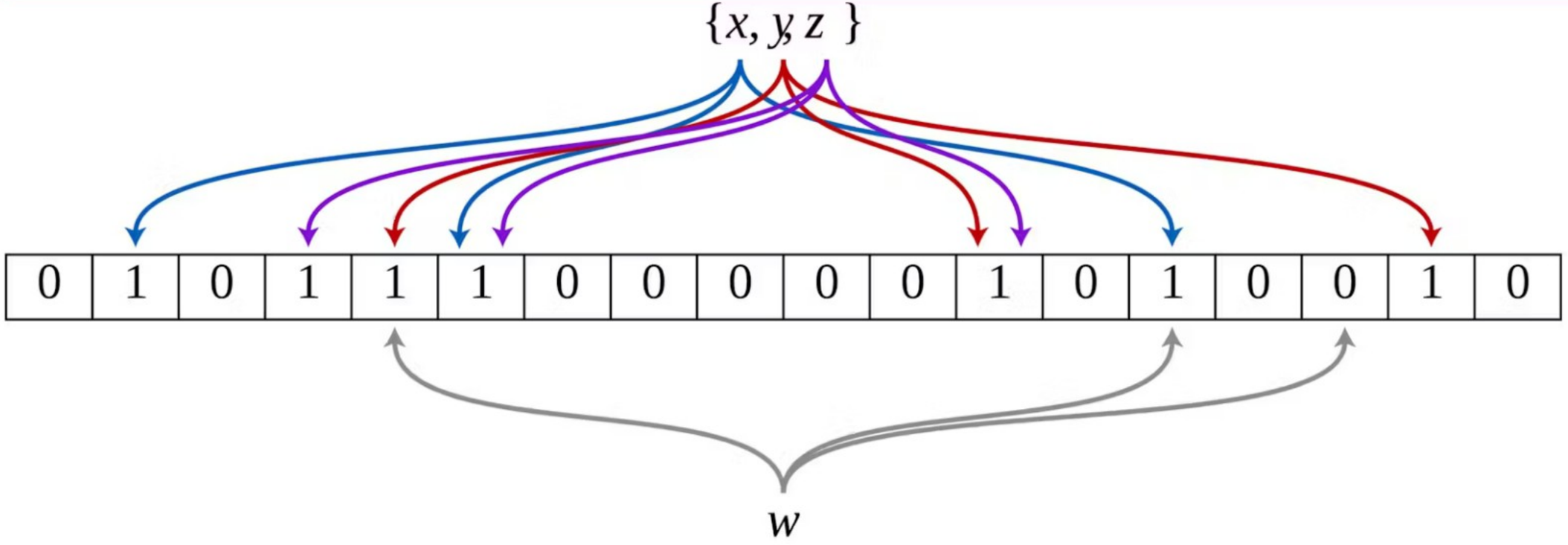
Bloom filters are called "filters" because they are used to filter out unnecessary data lookup in a database. They can quickly and efficiently tell if an element potentially exists in a set or definitely not. This helps in reducing the requirement to query the primary storage or database for data that positively do not exist.

HOW DOES A BLOOM FILTER WORK?



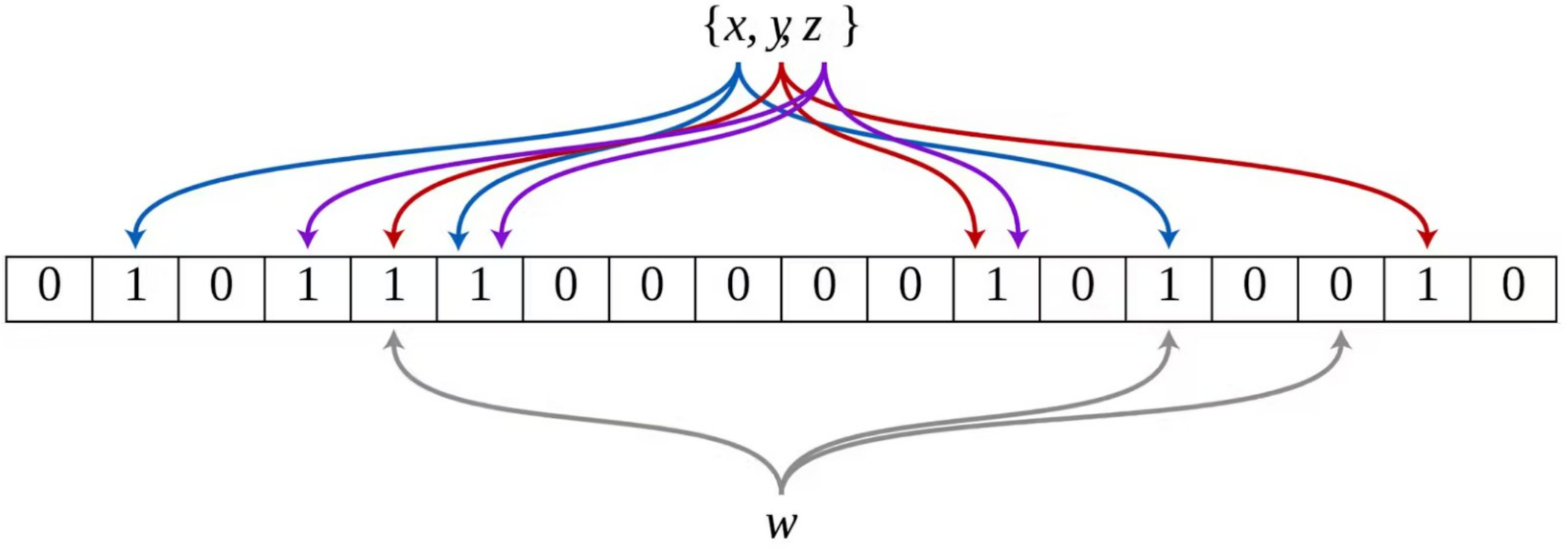
- Initizlize an empty array of size m and set all the values to 0
- **Adding elements**: Assume you have k hash functions. When you add an item, hash the value k times with the k functions and flag the resulting indeces as present.
- **Checking for presence**: Use the same k hash functions as when you added elements. Hash the input value k times. If all the k indeces are flagged, you probably have the value. If 1 or more are not flagged, you 100% don't have the value.

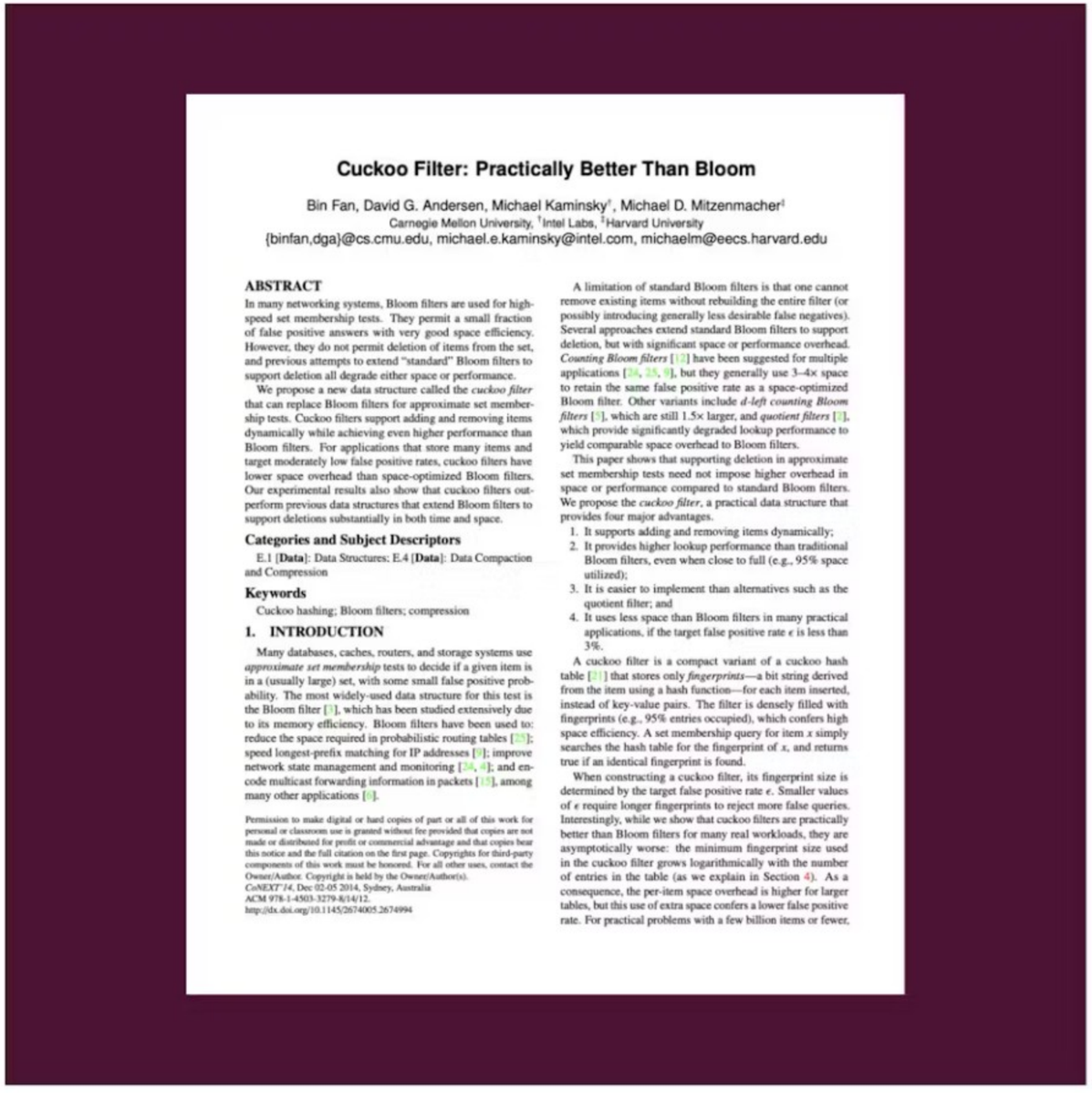
<- example explenation: m is 3 (because we have 3 bits) and k is 2 (because there are 2 hash functions)



WHY CAN BLOOM FILTERS GIVE FALSE POSITIVES?

WHY CAN YOU NOT DELETE ITEMS FROM BLOOM FILTERS?





Cuckoo Filter: Practically Better Than Bloom

Bin Fan, David G. Andersen, Michael Kaminsky†, Michael D. Mitzenmacher‡
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ABSTRACT

In many networking systems, Bloom filters are used for high-speed set membership tests. They permit a small fraction of false positive answers with very good space efficiency. However, they do not permit deletion of items from the set, and previous attempts to extend "standard" Bloom filters to support deletion all degrade either space or performance.

We propose a new data structure called the *cuckoo filter* that can replace Bloom filters for approximate set membership tests. Cuckoo filters support adding and removing items dynamically while achieving even higher performance than Bloom filters. For applications that store many items and target moderately low false positive rates, cuckoo filters have lower space overhead than space-optimized Bloom filters. Our experimental results also show that cuckoo filters outperform previous data structures that extend Bloom filters to support deletions substantially in both time and space.

Categories and Subject Descriptors

E.1 [**Data**]: Data Structures; E.4 [**Data**]: Data Compaction and Compression

Keywords

Cuckoo hashing; Bloom filters; compression

1. INTRODUCTION

Many databases, caches, routers, and storage systems use *approximate set membership* tests to decide if a given item is in a (usually large) set, with some small false positive probability. The most widely-used data structure for this test is the Bloom filter [3], which has been studied extensively due to its memory efficiency. Bloom filters have been used to: reduce the space required in probabilistic routing tables [25]; speed longest-prefix matching for IP addresses [9]; improve network state management and monitoring [24, 4]; and encode multicast forwarding information in packets [15], among many other applications [6].

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ACM 978-1-4503-3279-8/14/12.
http://dx.doi.org/10.1145/2674005.2674994

A limitation of standard Bloom filters is that one cannot remove existing items without rebuilding the entire filter (or possibly introducing generally less desirable false negatives). Several approaches extend standard Bloom filters to support deletion, but with significant space or performance overhead. *Counting Bloom filters* [12] have been suggested for multiple applications [26, 25, 9], but they generally use 3–4× space to retain the same false positive rate as a space-optimized Bloom filter. Other variants include *d-left counting Bloom filters* [5], which are still 1.5× larger, and *quotient filters* [2], which provide significantly degraded lookup performance to yield comparable space overhead to Bloom filters.

This paper shows that supporting deletion in approximate set membership tests need not impose higher overhead in space or performance compared to standard Bloom filters. We propose the *cuckoo filter*, a practical data structure that provides four major advantages.

1. It supports adding and removing items dynamically;
2. It provides higher lookup performance than traditional Bloom filters, even when close to full (e.g., 95% space utilized);
3. It is easier to implement than alternatives such as the quotient filter; and
4. It uses less space than Bloom filters in many practical applications, if the target false positive rate ϵ is less than 3%.

A cuckoo filter is a compact variant of a cuckoo hash table [21] that stores only *fingerprints*—a bit string derived from the item using a hash function—for each item inserted, instead of key-value pairs. The filter is densely filled with fingerprints (e.g., 95% entries occupied), which confers high space efficiency. A set membership query for item x simply searches the hash table for the fingerprint of x, and returns true if an identical fingerprint is found.

When constructing a cuckoo filter, its fingerprint size is determined by the target false positive rate ϵ. Smaller values of ϵ require longer fingerprints to reject more false queries. Interestingly, while we show that cuckoo filters are practically better than Bloom filters for many real workloads, they are asymptotically worse: the minimum fingerprint size used in the cuckoo filter grows logarithmically with the number of entries in the table (as we explain in Section 4). As a consequence, the per-item space overhead is higher for larger tables, but this use of extra space confers a lower false positive rate. For practical problems with a few billion items or fewer,

CUCKOO FILTERS

- "Bloom filters but better"
- Allows deleting items
- Use even less memory
- New datastructure, first described in 2014

CUCKOO FILTERS

Cuckoo hashing

Article Talk

From Wikipedia, the free encyclopedia

Cuckoo hashing is a scheme in computer programming for resolving hash collisions of values of hash functions in a table, with worst-case constant lookup time. The name derives from the behavior of some species of cuckoo, where the cuckoo chick pushes the other eggs or young out of the nest when it hatches in a variation of the behavior referred to as brood parasitism; analogously, inserting a new key into a cuckoo hashing table may push an older key to a different location in the table.

- Why cuckoo?
  - Because of the underlying cuckoo hashing
- Why filter?
  - Probably to filter out unneeded expensive work like with Bloom filters.

HOW CUCKOO FILTERS WORK DIFFERENTLY FROM BLOOM FILTERS?

- Main difference lies in the hashing algorithm
  - Described in 2001.
    - Recall that the cuckoo filters appeard in 2014.
  - Cuckoo hashing is not relevant for the course - not covered in detail. See the paper if interested.

  - They outline 4 advantages in the paper:
    - It supports adding and removing items dynamically
    - It provides higher lookup performance than traditional Bloom filters, even when close to full (e.g., 95% space utilized);
    - It is easier to implement than alternatives such as the quotient filter
    - It uses less space than Bloom filters in many practical applications, if the target false positive rate is less than 3%.

Live progge D-1?

Hva kan nå gå galt...

Neste gang:

- Repetisjon
- *Vurderer gruppearbeid*
- TDB (kom gjerne med innspill)
- SVMer? Compression? ANN?

Assignment workshop. Write something here and we'll discuss it towards the end.

Break until 15:15 😄