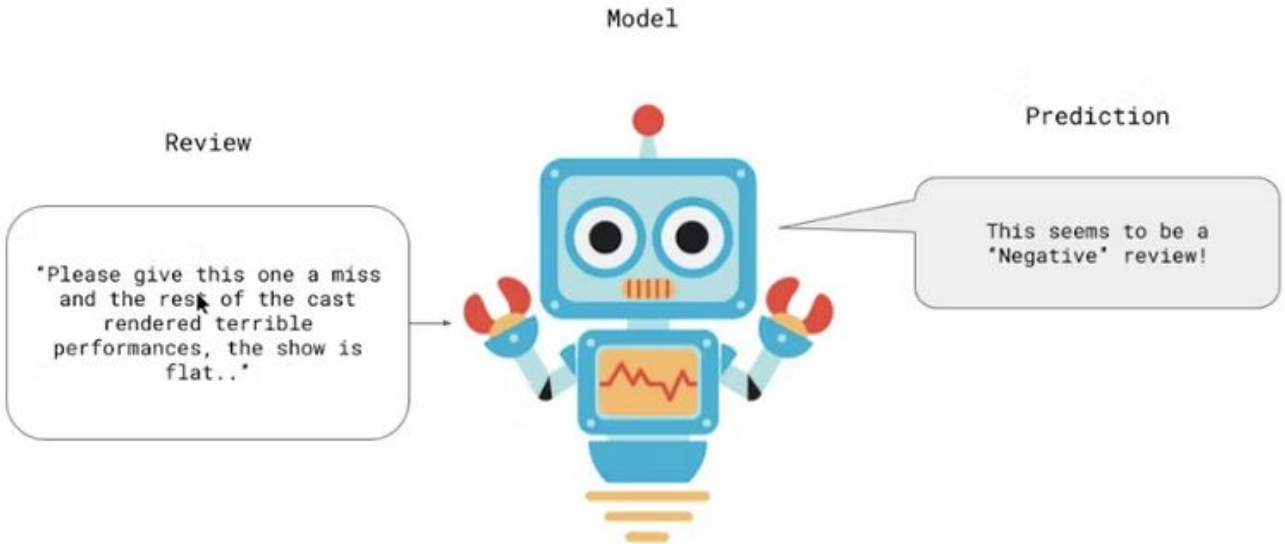
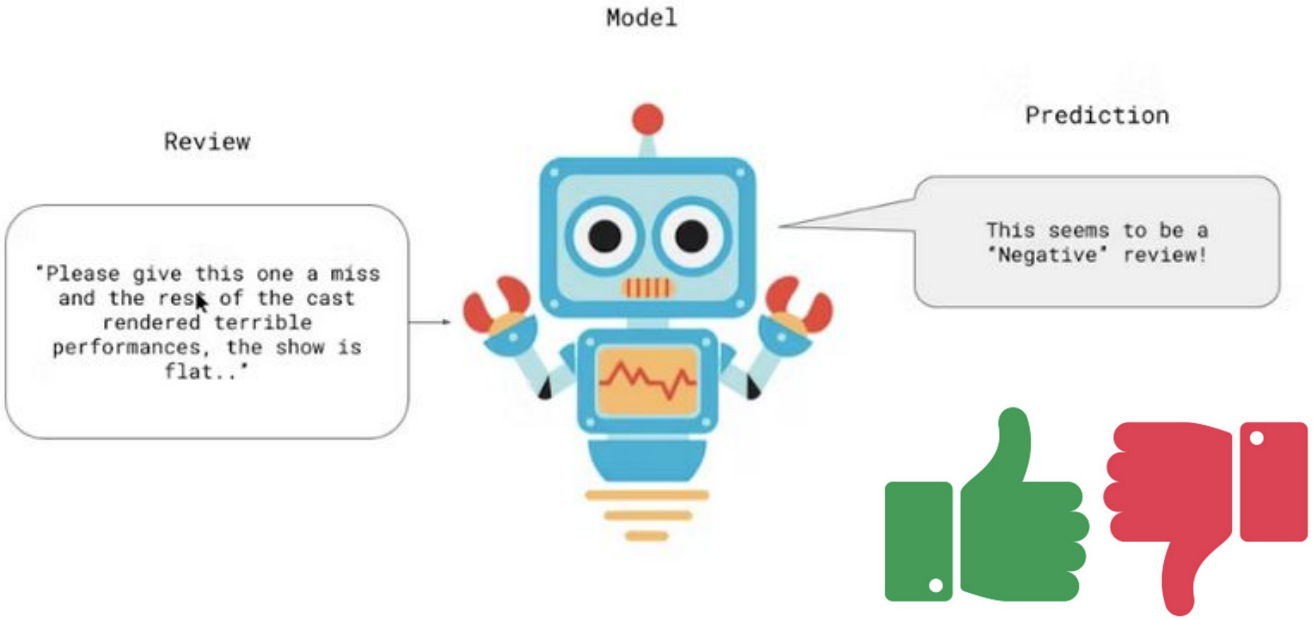
Sentiment Analysis


Model
Review
"Please give this one a miss and the rest of the cast rendered terrible performances, the show is flat.."
Prediction
This seems to be a 'Negative' review!

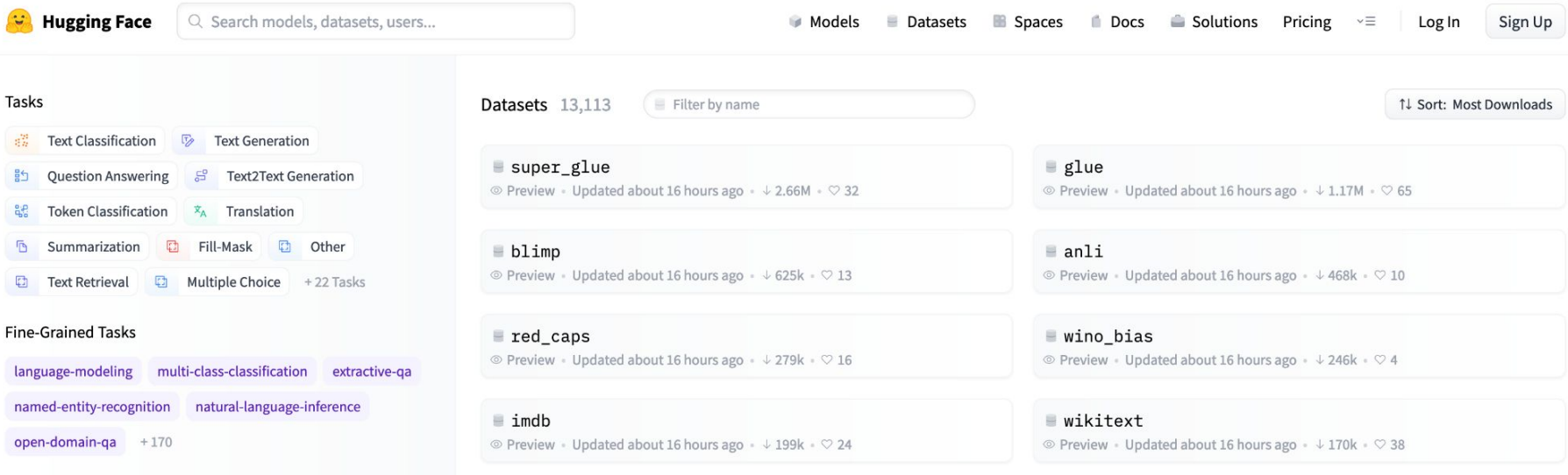
Binary classification



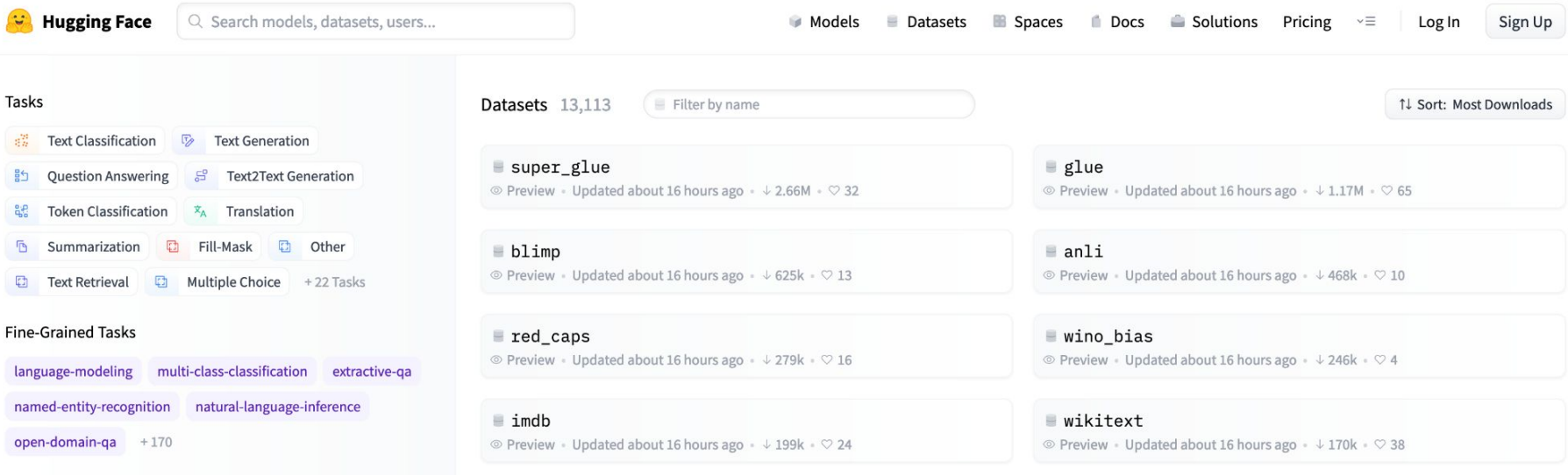
Labeled dataset

text (string)	label (class label)
"I love sci-fi and am willing to put up with a lot. Sci-fi movies/TV are usually underfunded, under-appreciated and misunderstood. I tried to like…	0 (neg)
"Worth the entertainment value of a rental, especially if you like action movies. This one features the usual car chases, fights with the great Van…	0 (neg)
"its a totally average film with a few semi-alright action sequences that make the plot seem a little better and remind the viewer of the classic va…	0 (neg)
"STAR RATING: ***** Saturday Night **** Friday Night *** Friday Morning ** Sunday Night * Monday Morning Former New Orleans homicide cop…	0 (neg)

Labeled dataset



Labeled dataset



NLP - as a Service

Sentiment Analysis - as a Service

Amazon Comprehend:
Sentiment Analysis API

▼ **Results**

Sentiment

Neutral	Positive	Negative	Mixed
0.01 confidence	0.83 confidence	0.02 confidence	0.13 confidence

▼ **Application integration**

API call and API response of DetectSentiment API. Info

API call

```
{
    "Text": "52-Pick Up never got the respect it
        should have.\nIt works on many levels, and has
        a complicated but\nfollowable plot. The actors
        involved give some of\ntheir finest
        performances. Ann-Margret, Roy\nScheider, and
        John Glover are perfectly cast and\nprovide
        deep character portrayals. Notable too
        are\nVanity, who should have parlayed this
        into a\nserious acting career given the
        unexpected ability\nshe shows, and Kelly
        Preston, who's character will\nhaunt you for a
        few days. Anyone who likes action\ncombined
        with a gritty complicated story will\nenjoy
        this.",
    "LanguageCode": "en"
}
```

API response

```
{
    "Sentiment": {
        "Sentiment": "POSITIVE",
        "SentimentScore": {
            "Positive": 0.8310282826423645,
            "Negative": 0.024984251707792282,
            "Neutral": 0.011633211746811867,
            "Mixed": 0.1323542594909668
        }
    }
}
```

Issues

Issues

- What to predict?
  - there is a vast number of sentiments and many nuances
  - most application simply into few categories: pos/neg/neutral or hate speech/non-hate
  - star rating: 1-5

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  - depends on culture, individuals, context
  - labelled data might be biased
  - extremes are easier to detect/agree upon - more interesting
  - Negative / Hate might be more important - minimize error

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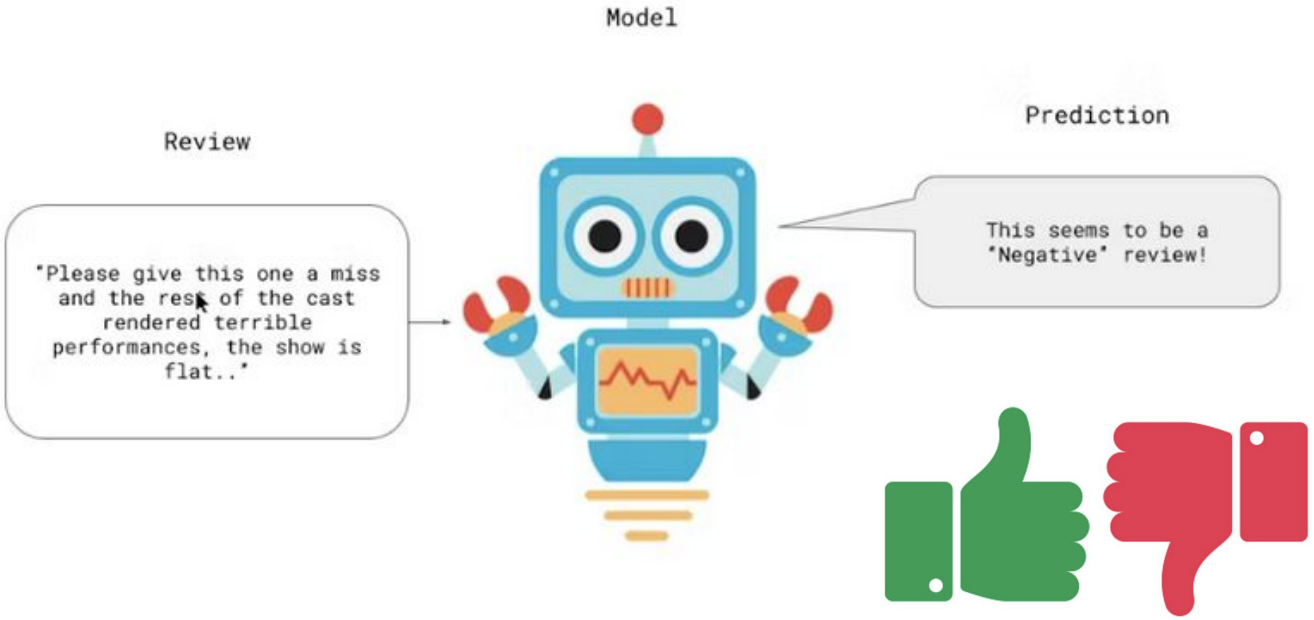
- How to aggregate?
  - Sentiment can change throughout a sentence/paragraph
  - Word - Sentence - Aspect/Topic - Document - levels - how to combine sentiment scores?
  - Simple average, weighted average, majority voting, Dempster-Shafer algorithm, uninorm operators

Evaluation

if you can’t evaluate,
maybe you shouldn't even start

Binary classification

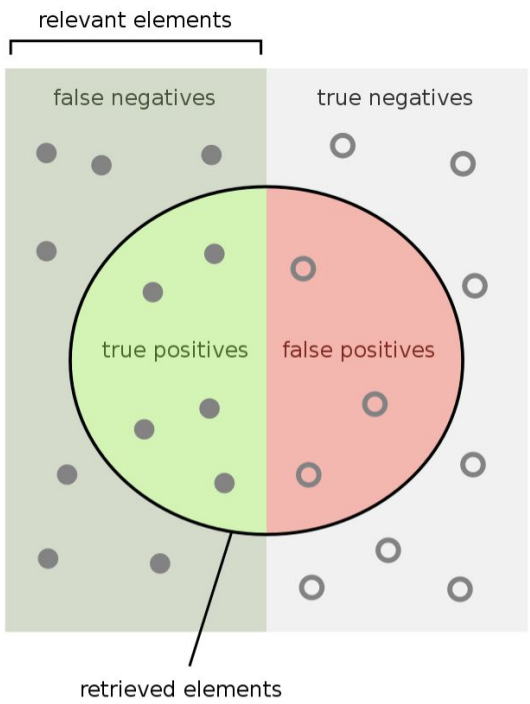


Evaluation

$$accuracy = \frac{correct}{correct + incorrect}$$

Evaluation

Evaluation



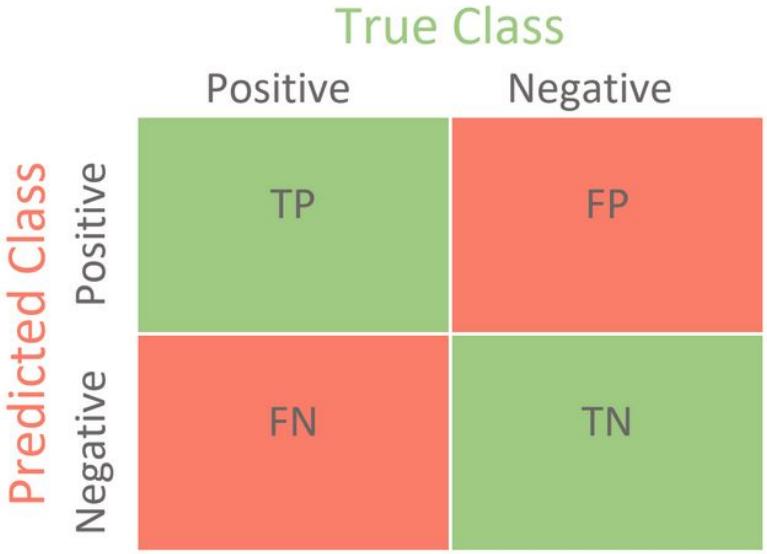
How many retrieved items are relevant?

$$\text{Precision} = \frac{\text{true positives}}{\text{retrieved elements}}$$

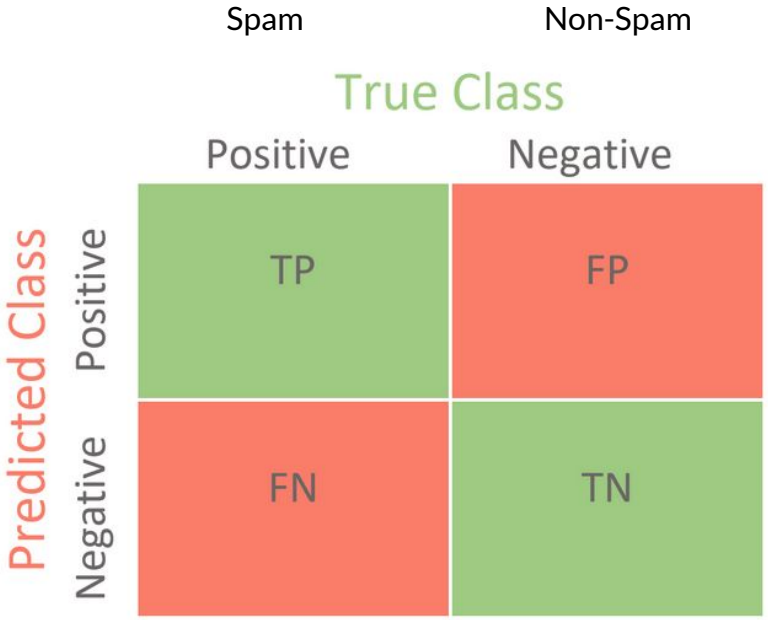
How many relevant items are retrieved?

$$\text{Recall} = \frac{\text{true positives}}{\text{relevant elements}}$$

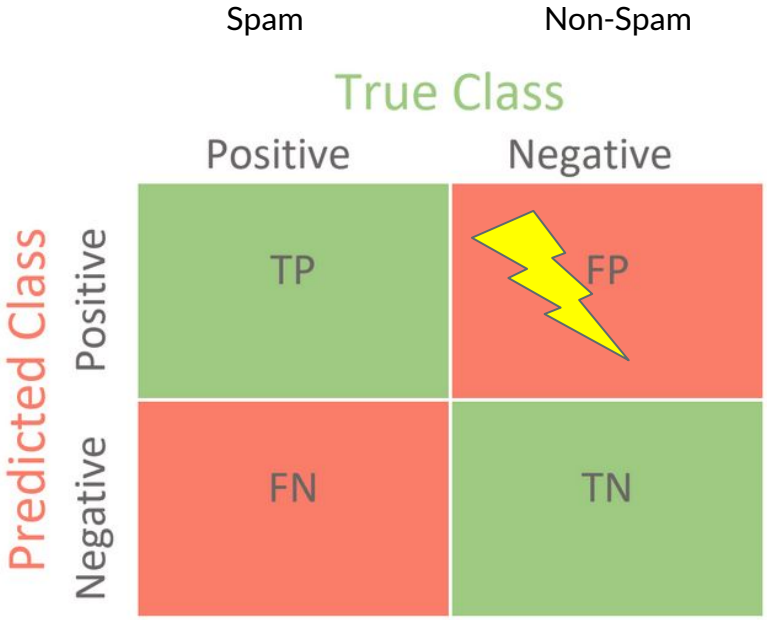
Evaluation


True Class
Positive
Negative
Predicted Class
Positive
Negative
TP
FP
FN
TN

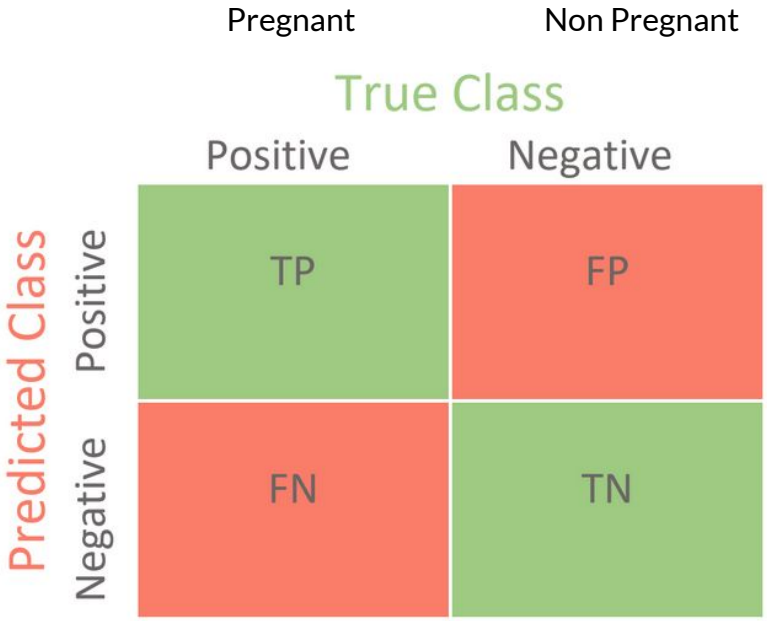
Evaluation


Spam
Non-Spam
True Class
Positive
Negative
Predicted Class
Positive
Negative
TP
FP
FN
TN

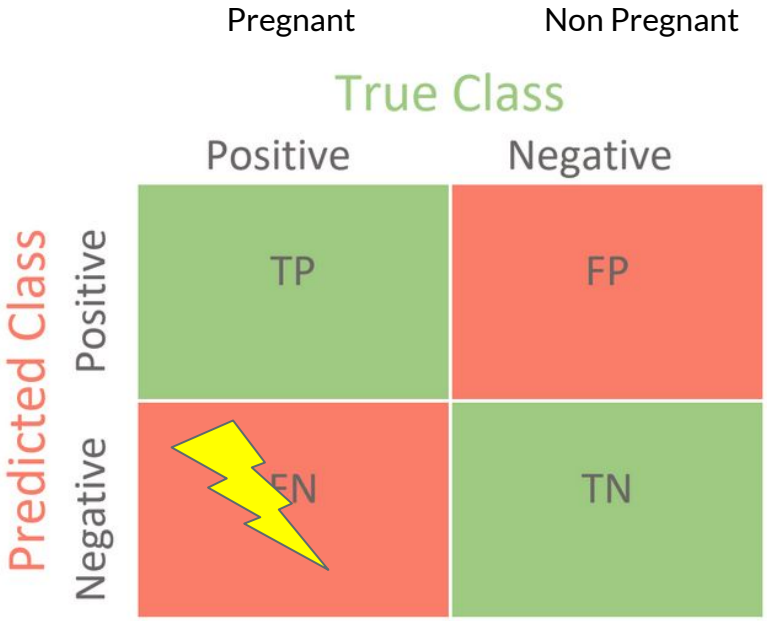
Evaluation


Spam
Non-Spam
True Class
Positive
Negative
Predicted Class
Positive
Negative
TP
FP
FN
TN

Evaluation


Pregnant
Non Pregnant
True Class
Positive
Negative
Predicted Class
Positive
Negative
TP
FP
FN
TN

Evaluation

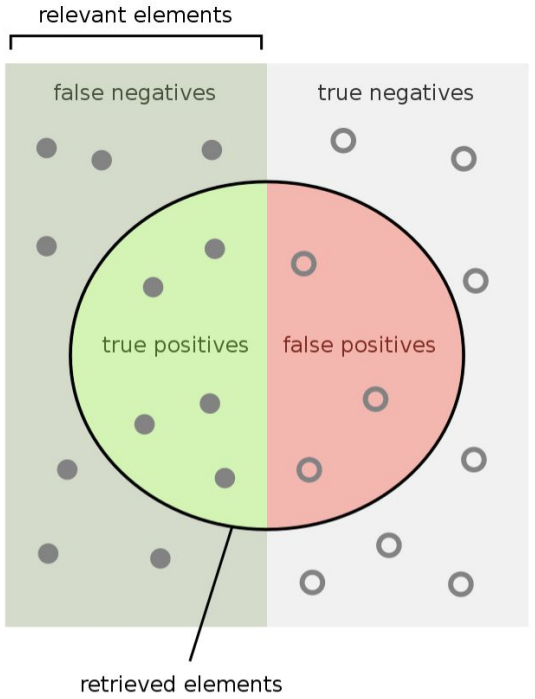

Pregnant
Non Pregnant
True Class
Positive
Negative
Predicted Class
Positive
Negative
TP
FP
FN
TN

Fairness

Evaluation

$$F1 = \frac{2 * precision * recall}{precision + recall}$$

$$F1 = \frac{2 \times 0.8 \times 0.2}{0.8 + 0.2} \quad \therefore F1=0.32$$



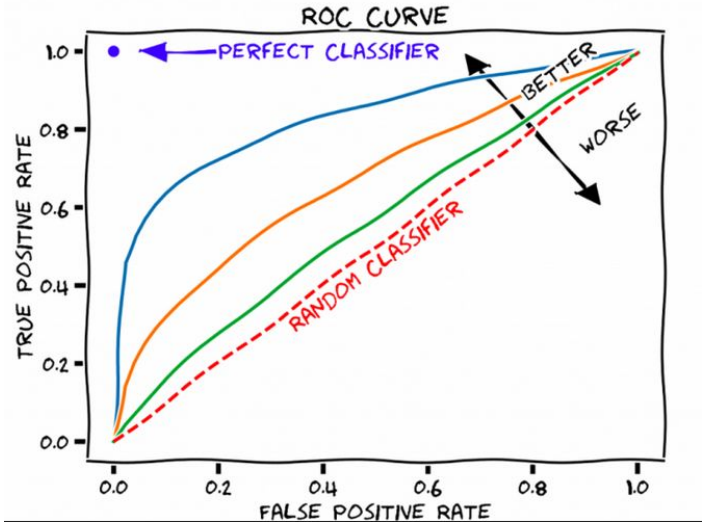
How many retrieved items are relevant?

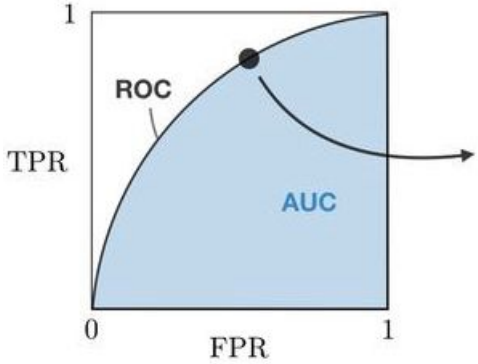
Precision =

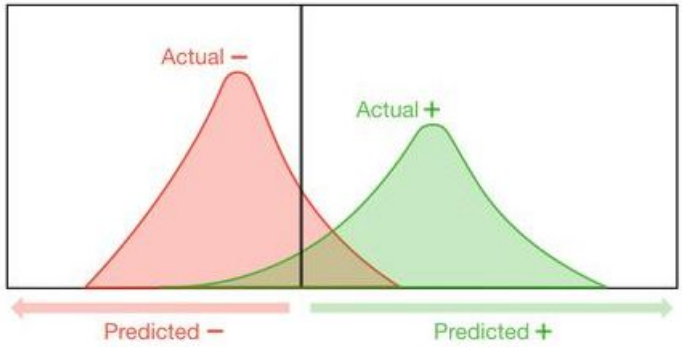
How many relevant items are retrieved?

Recall =

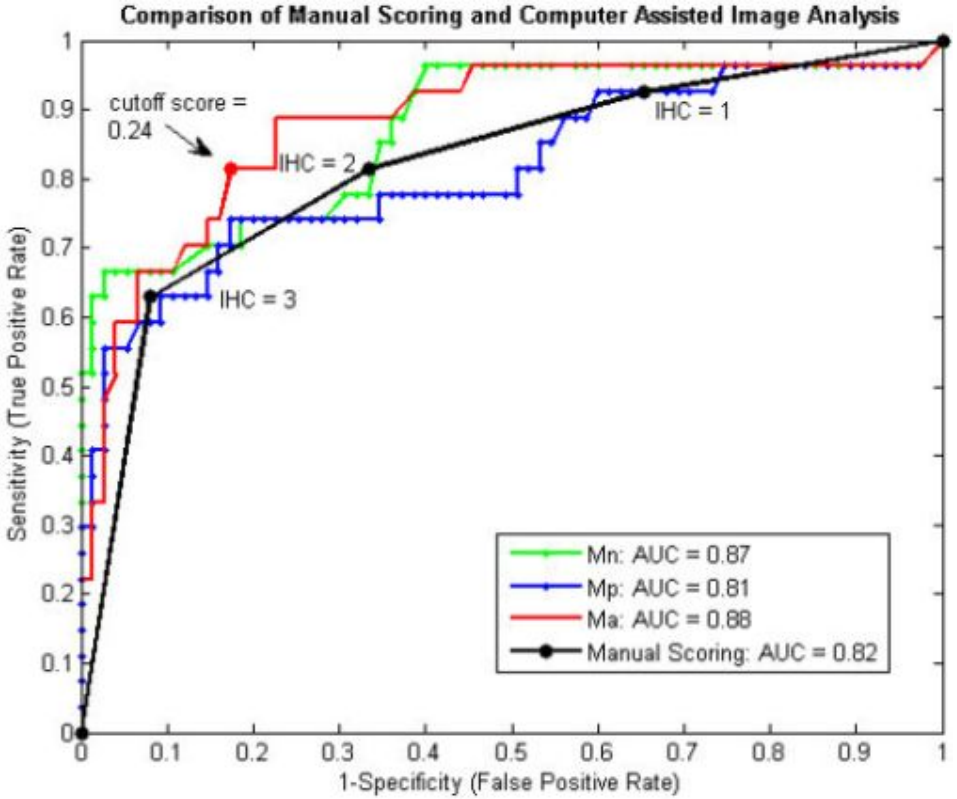
Evaluation


ROC CURVE
PERFECT CLASSIFIER
BETTER
WORSE
RANDOM CLASSIFIER
TRUE POSITIVE RATE
FALSE POSITIVE RATE
0.0
0.2
0.4
0.6
0.8
1.0

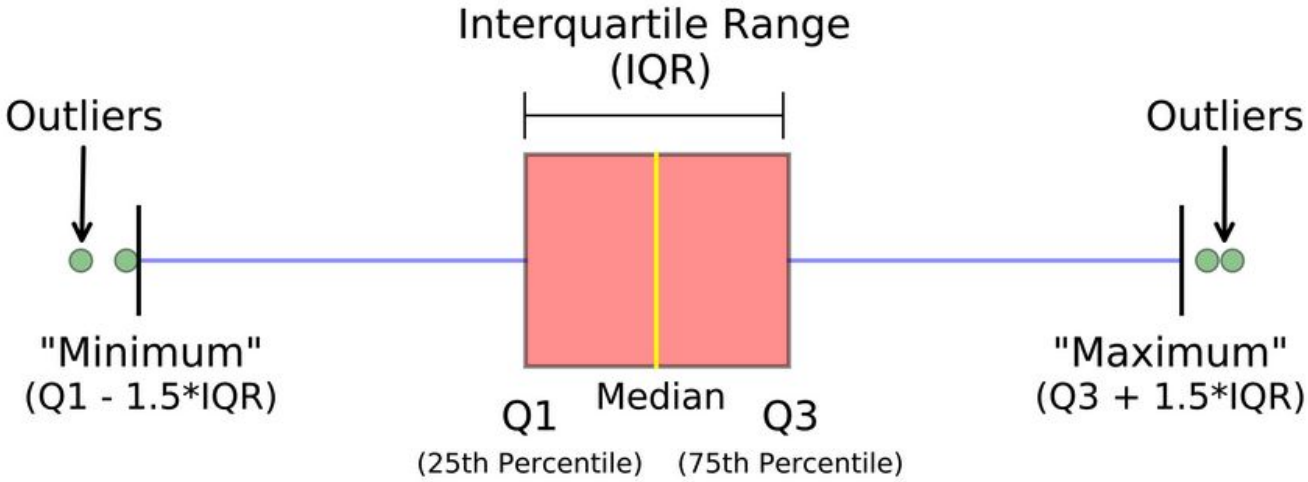

1
ROC
TPR
AUC
0
1
FPR


Actual −
Actual +
Predicted −
Predicted +

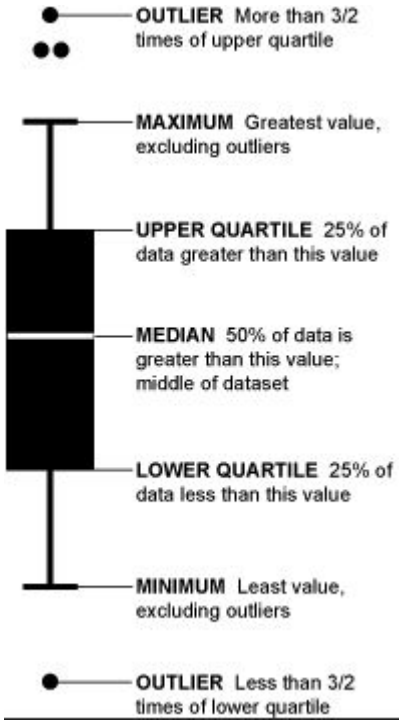
Evaluation


Comparison of Manual Scoring and Computer Assisted Image Analysis
cutoff score = 0.24
IHC = 1
IHC = 2
IHC = 3
Sensitivity (True Positive Rate)
1-Specificity (False Positive Rate)
Mn: AUC = 0.87
Mp: AUC = 0.81
Ma: AUC = 0.88
Manual Scoring: AUC = 0.82

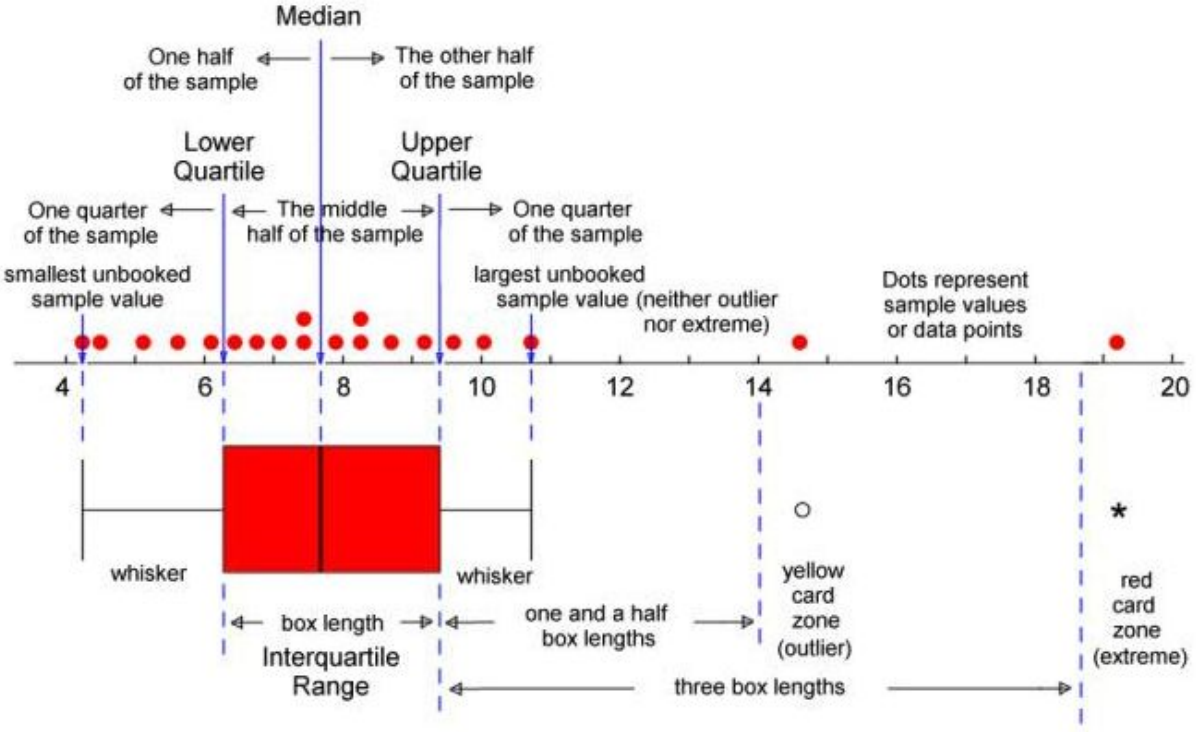
Boxplot


Interquartile Range
(IQR)
Outliers
Outliers
"Minimum"
(Q1 - 1.5*IQR)
Q1
Median
Q3
(25th Percentile)
(75th Percentile)
"Maximum"
(Q3 + 1.5*IQR)

Boxplot


OUTLIER More than 3/2 times of upper quartile
MAXIMUM Greatest value, excluding outliers
UPPER QUARTILE 25% of data greater than this value
MEDIAN 50% of data is greater than this value; middle of dataset
LOWER QUARTILE 25% of data less than this value
MINIMUM Least value, excluding outliers
OUTLIER Less than 3/2 times of lower quartile

Boxplot


Median
One half of the sample
The other half of the sample
Lower Quartile
Upper Quartile
One quarter of the sample
The middle half of the sample
One quarter of the sample
smallest unbooked sample value
largest unbooked sample value (neither outlier nor extreme)
Dots represent sample values or data points
4
6
8
10
12
14
16
18
20
whisker
whisker
box length
Interquartile Range
one and a half box lengths
yellow card zone (outlier)
red card zone (extreme)
three box lengths

Tokenization

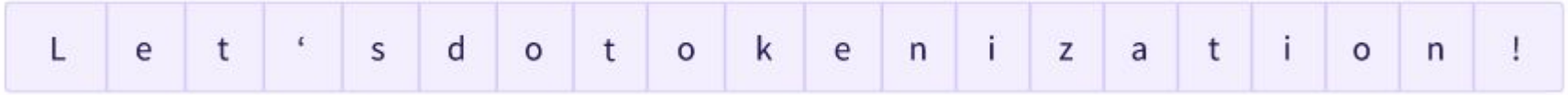
Let's	do	tokenization!

Tokenization

Computationally Expensive
Too many words

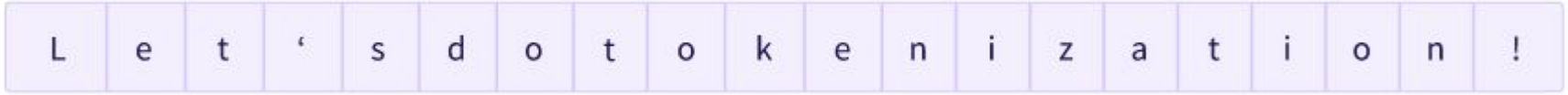
Limit vocabulary
Loose input information

Tokenization



Tokenization

Loose linguistic information
Words need to be relearnt



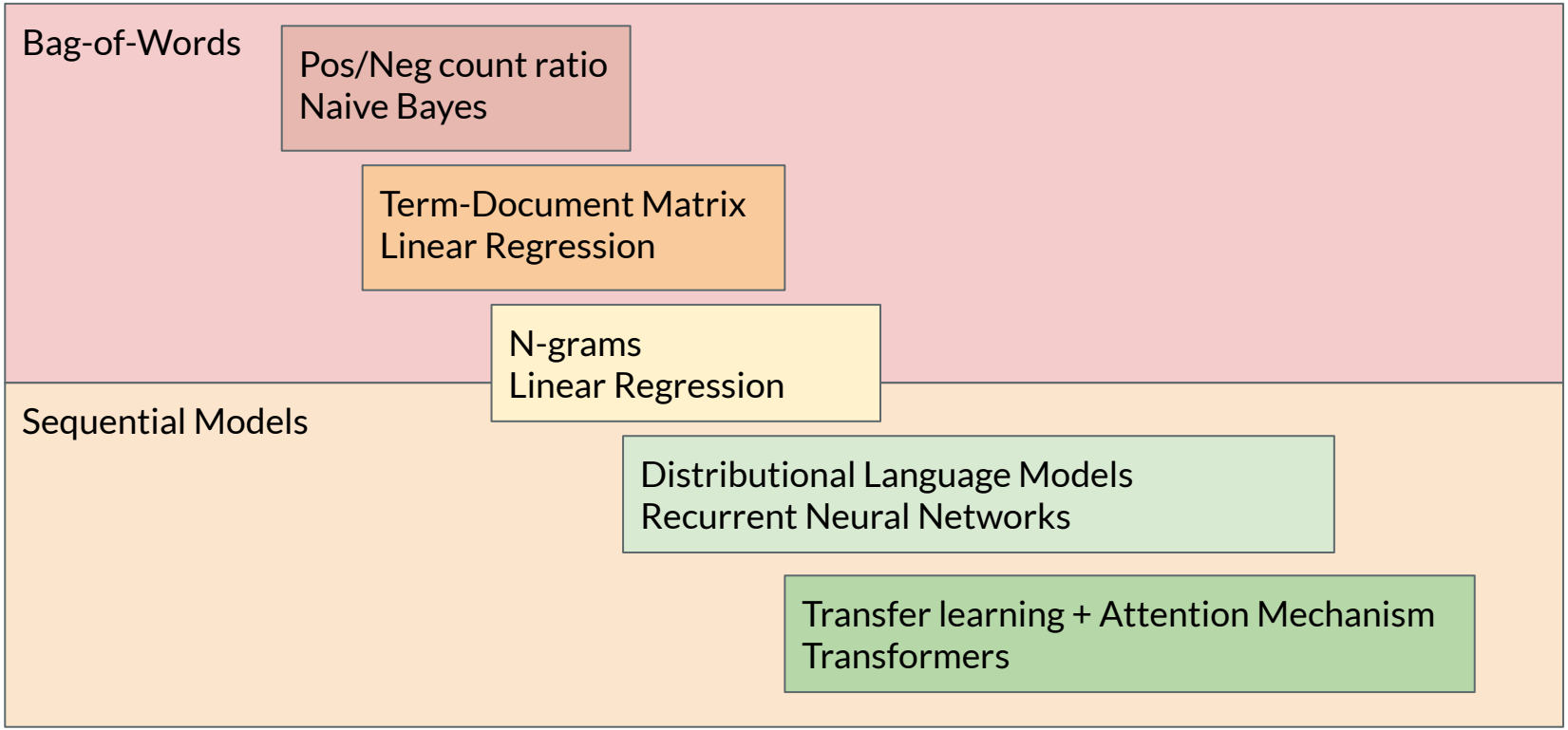
Increased training time
Increased training data needed

Tokenization

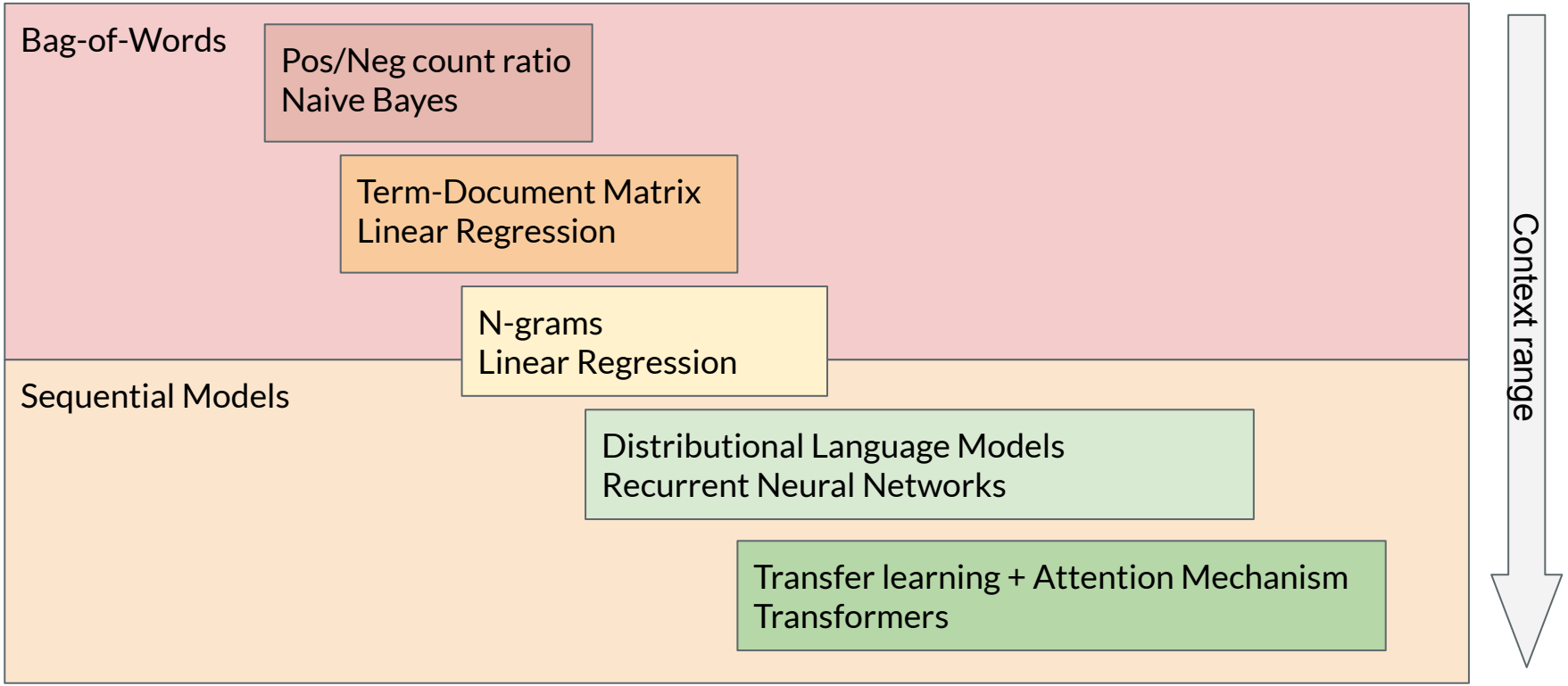
Preserves semantic meaning
Frequent words are preserved

Space efficient
Rare words are split up

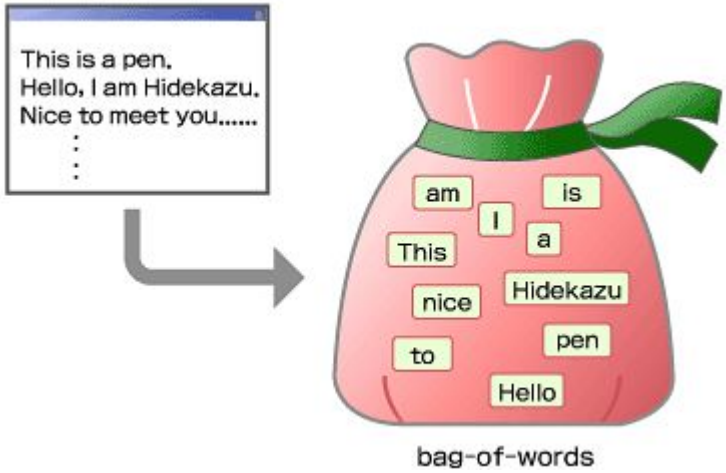
Solution Tiers



Solution Tiers



Bag-of-Words


This is a pen.
Hello, I am Hidekazu.
Nice to meet you.....
am
is
I
a
This
Hidekazu
nice
pen
to
Hello
bag-of-words

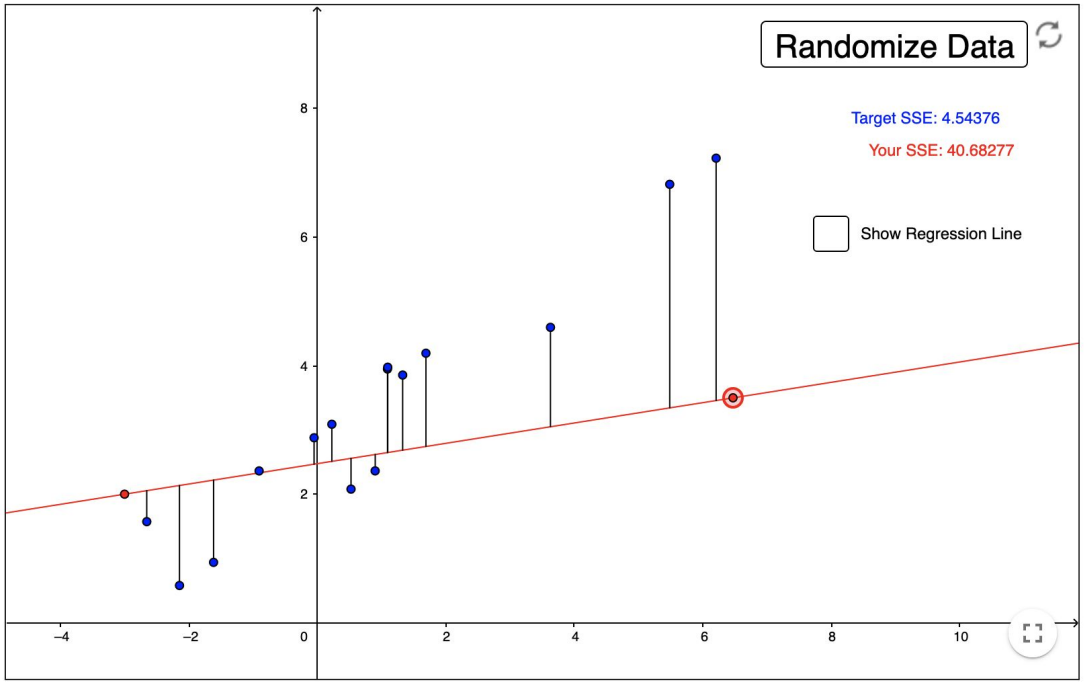
Bag-of-Words

Word	Positive Probability Count	Negative Probability Count	Ratio
problem	2/100	10/100	0.2
best	10/100	1/100	10
slowly	5/100	6/100	0.83

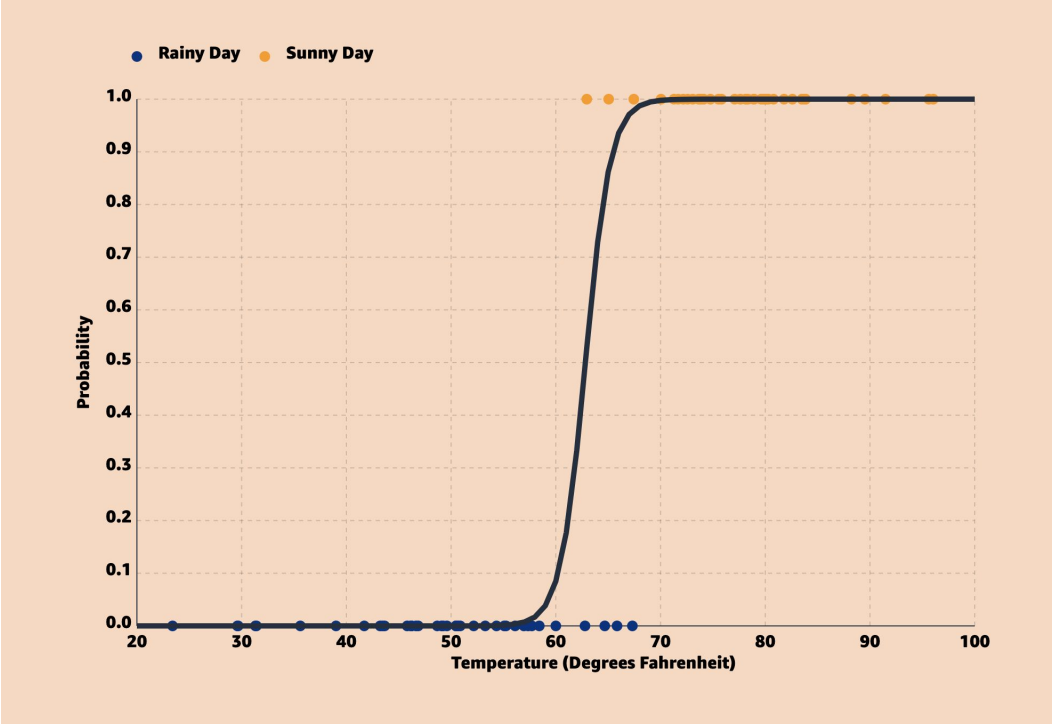
Bag-of-Words

	the	red	dog	cat	eats	food
1. the red dog →	1	1	1	0	0	0
2. cat eats dog →	0	0	1	1	1	0
3. dog eats food →	0	0	1	0	1	1
4. red cat eats →	0	1	0	1	1	0

Linear Regression



Logistic Regression



Logistic Regression

Sigmoid -> Prediction

- takes [-inf,inf] and converts to (0,1)
- with a rate of change - bigger around 0.5 uncertainty, then at 0 or 1 more certainty
- Why this specific formula? Why use e (=Euler's number 2.71)?
  - because to use standard training (SGD) we need a continuous & differentiable function
  - and because using this formula with e, the derivative is simple!!
  - d(a^x)/dx = a^x * ln(a)
  - d(e^x)/dx = e^x

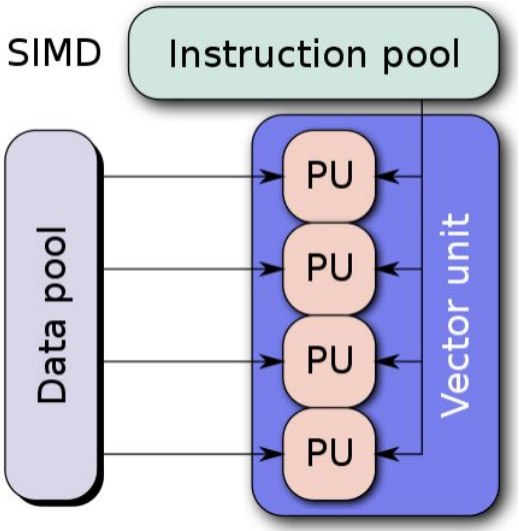
Logistic Regression

Log-Loss/Binary Cross-Entropy -> Evaluation

- cost function - ylog(pred) + (1-y)log(1-pred)
  - prediction between 0-1 => log between -inf-0

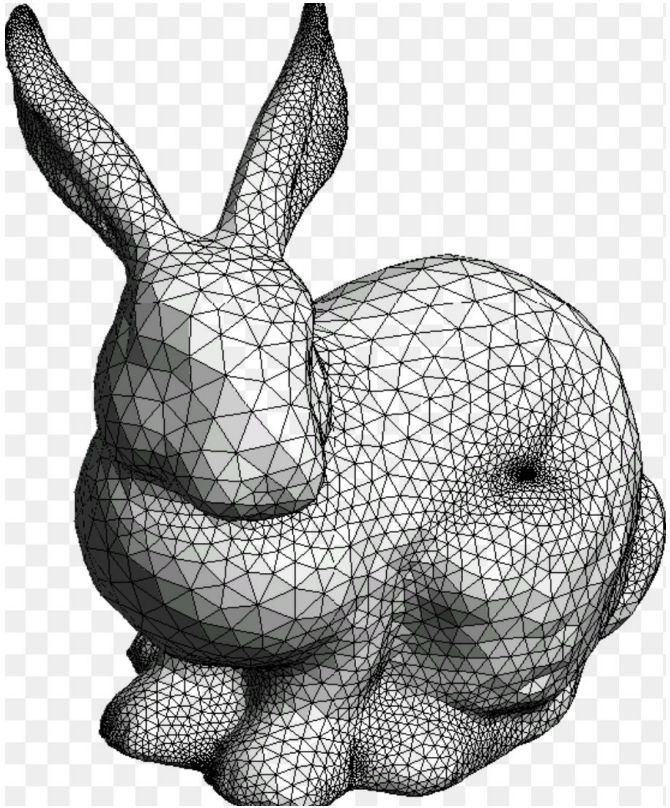
Vectorization == SIMD

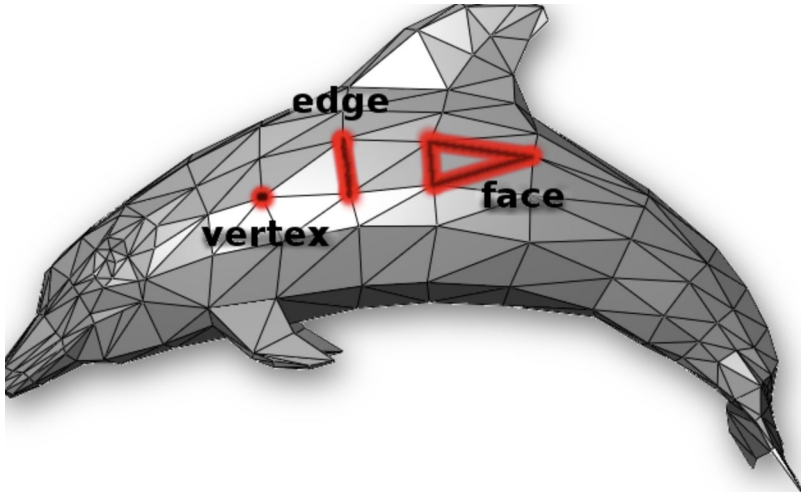
Modern CPUs supports operations for SIMD (Single Instructions on Multiple Data)



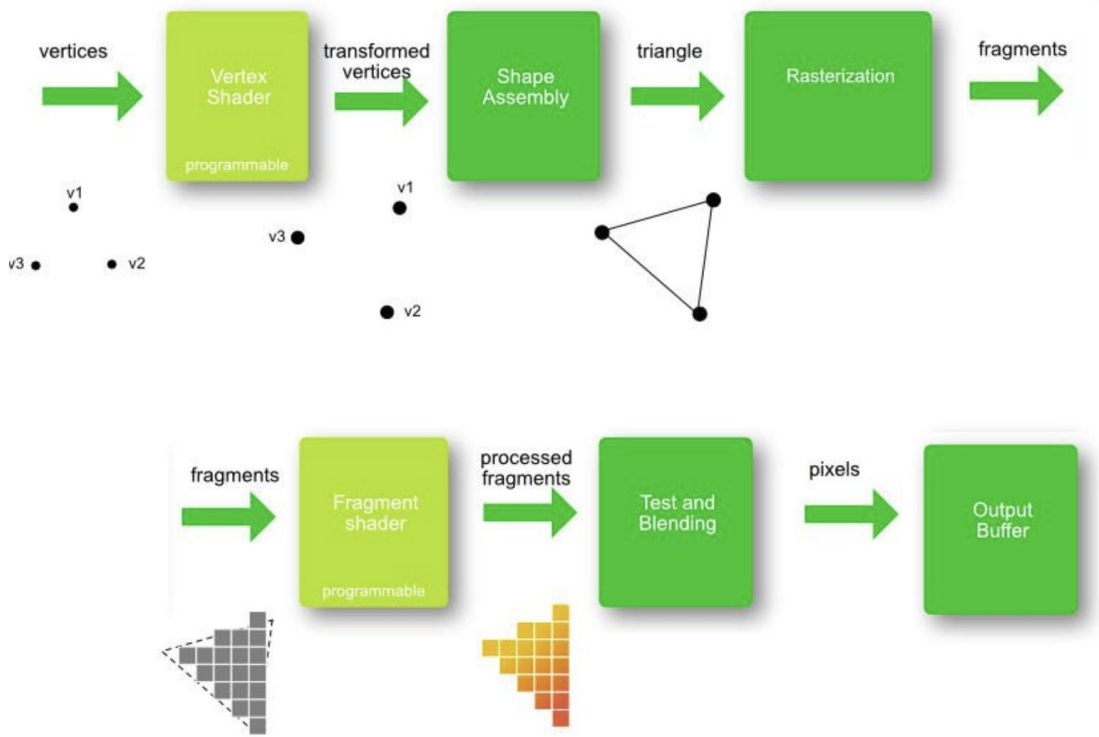
Single Data vs Multiple Data Instructions

GPU



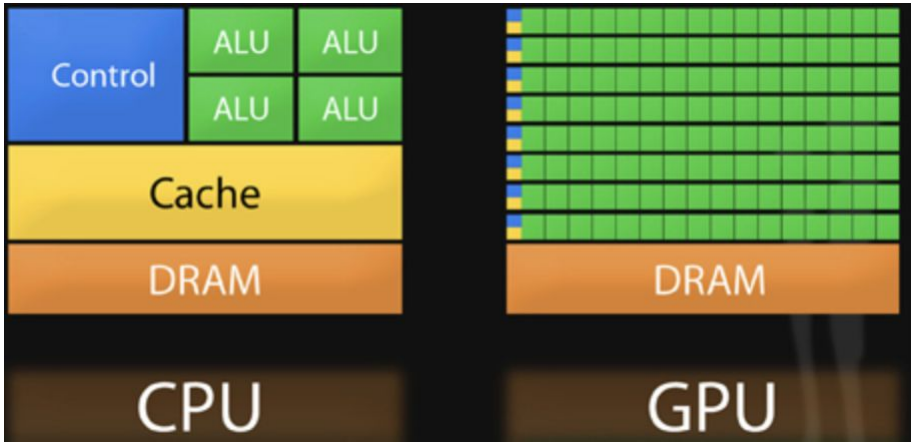


GPU - specialized hardware for coloring triangles



CPU vs GPU

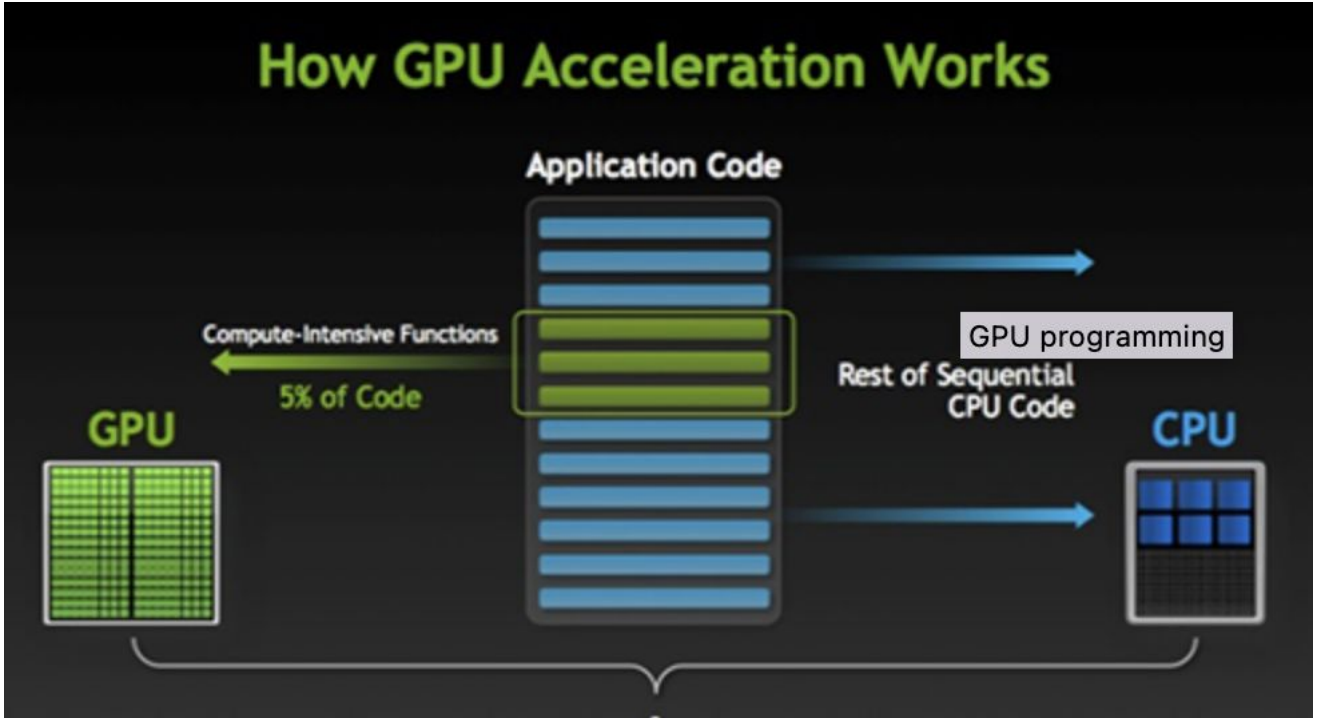
Arithmetic Logical Units (4 vs 1000)



GPU is designed for *data-parallel computations*

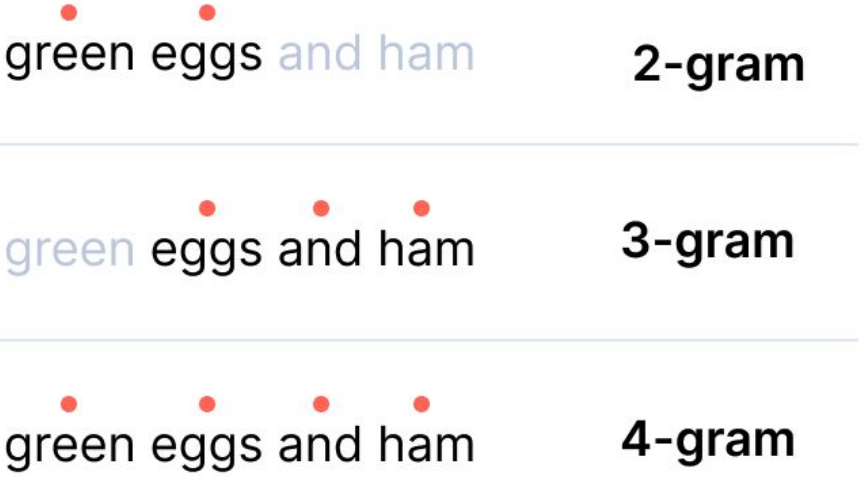
- same program executed on many data elements in parallel
  - no need for sophisticated flow control
- high ratio of arithmetic operations to memory operations
  - no need for lots of cache to speed up memory access

GPU Acceleration

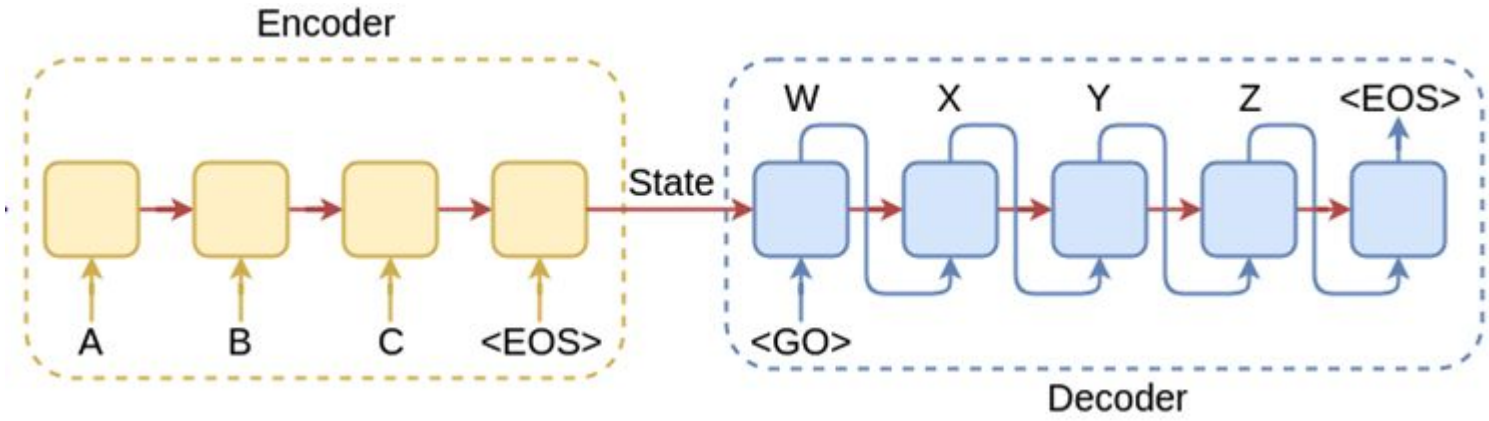


N-Grams

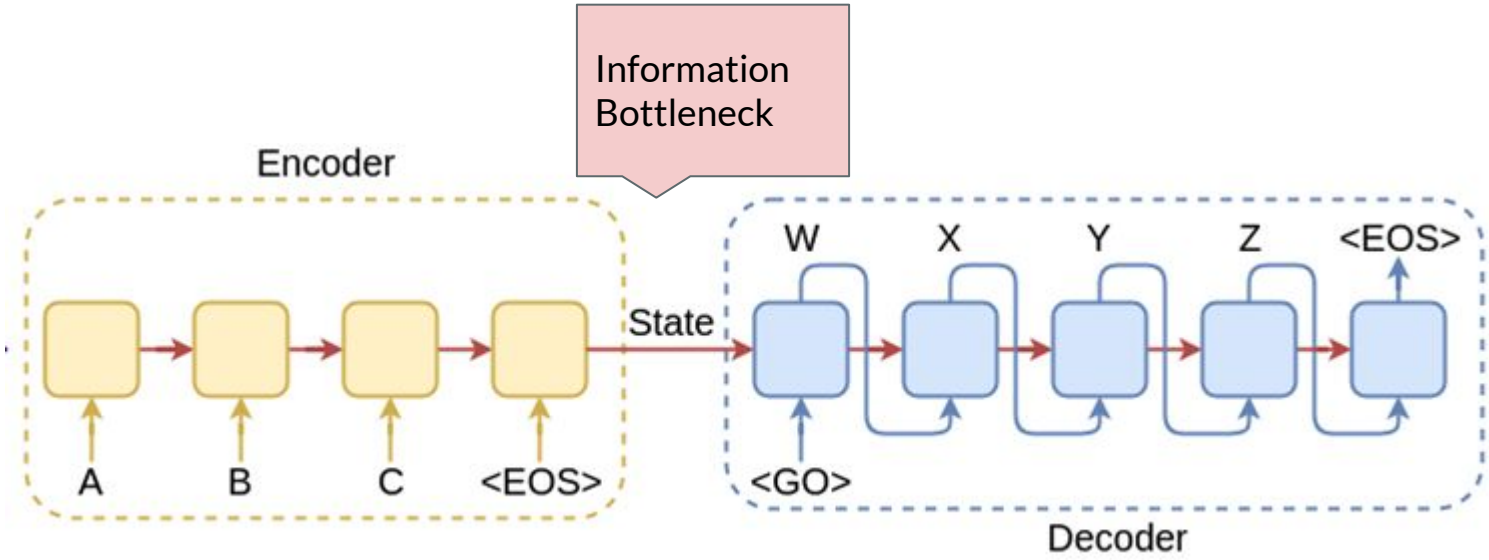
N-grams are a sequence of n tokens from a sample of text.



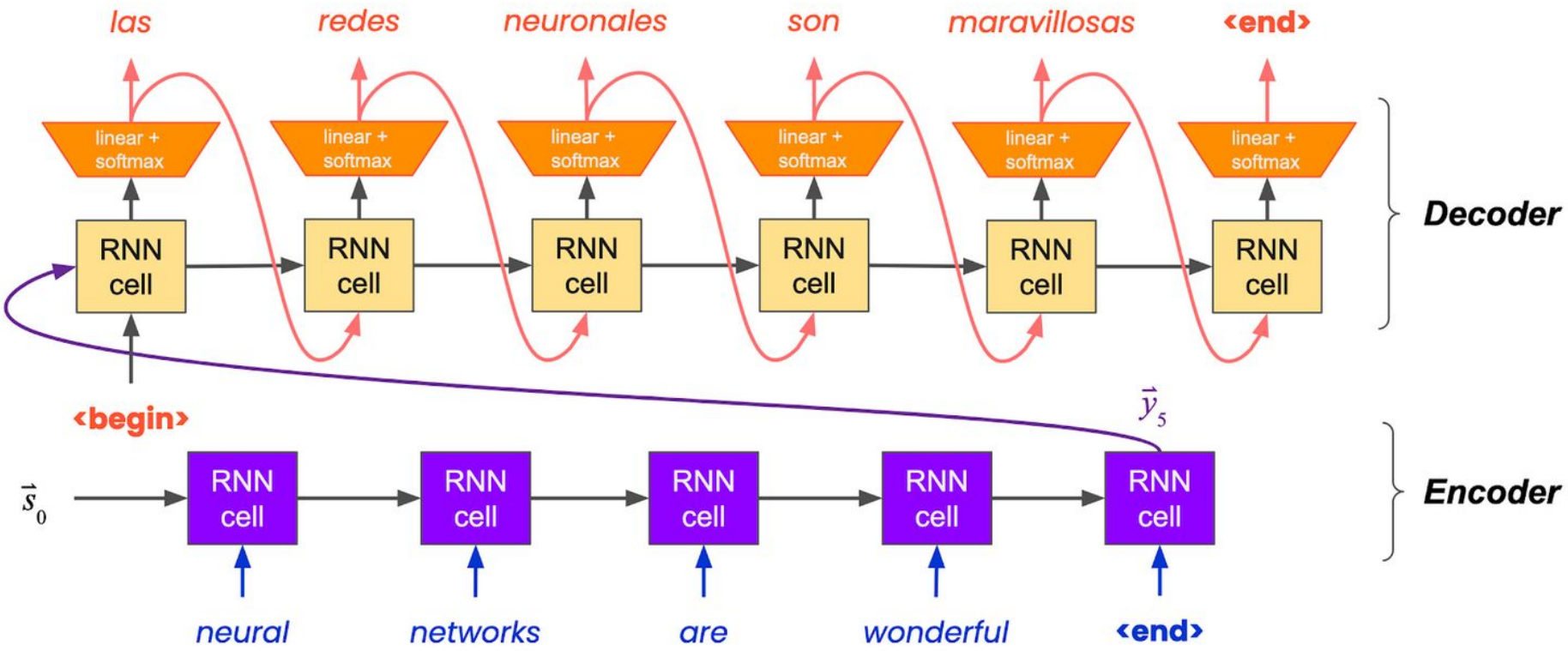
Sequential Models



Sequential Models

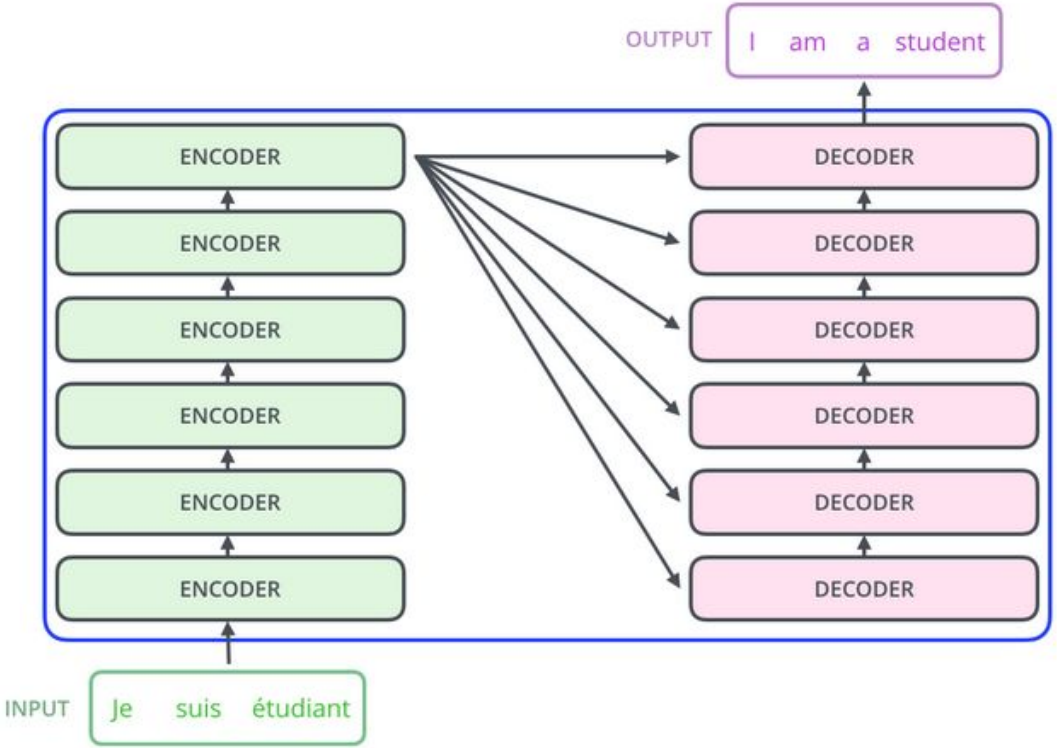


Sequential Models

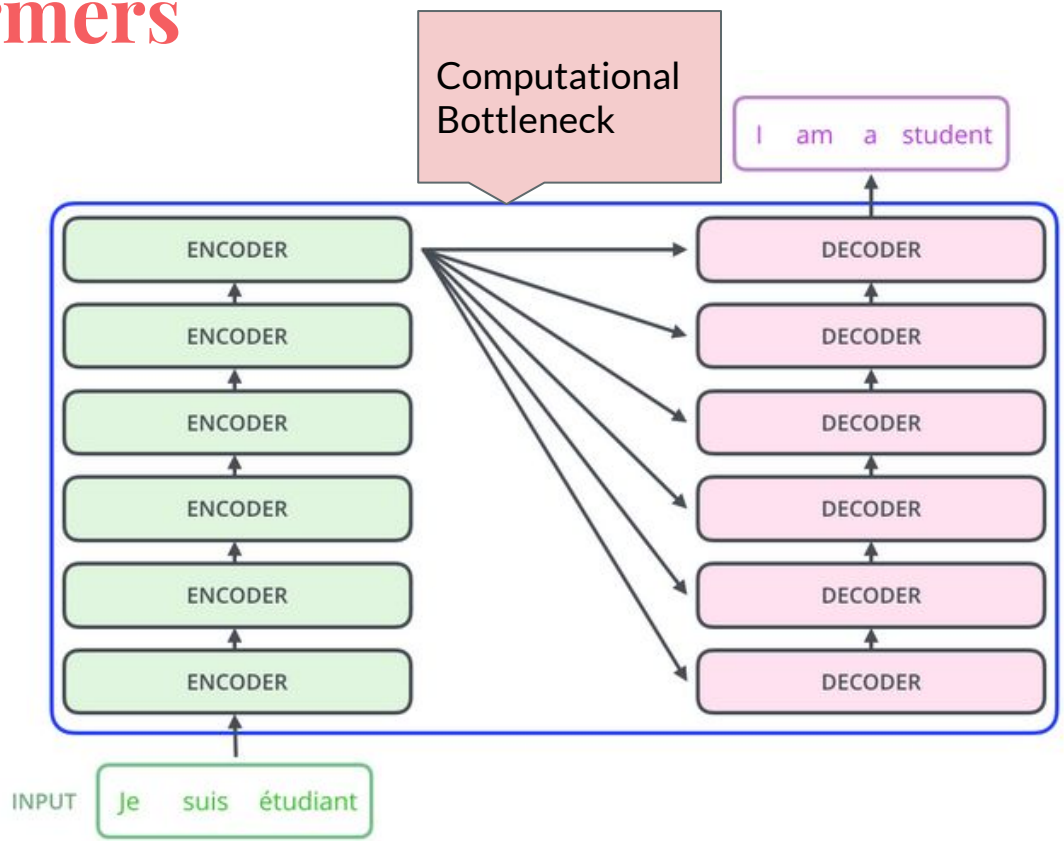


Transformers

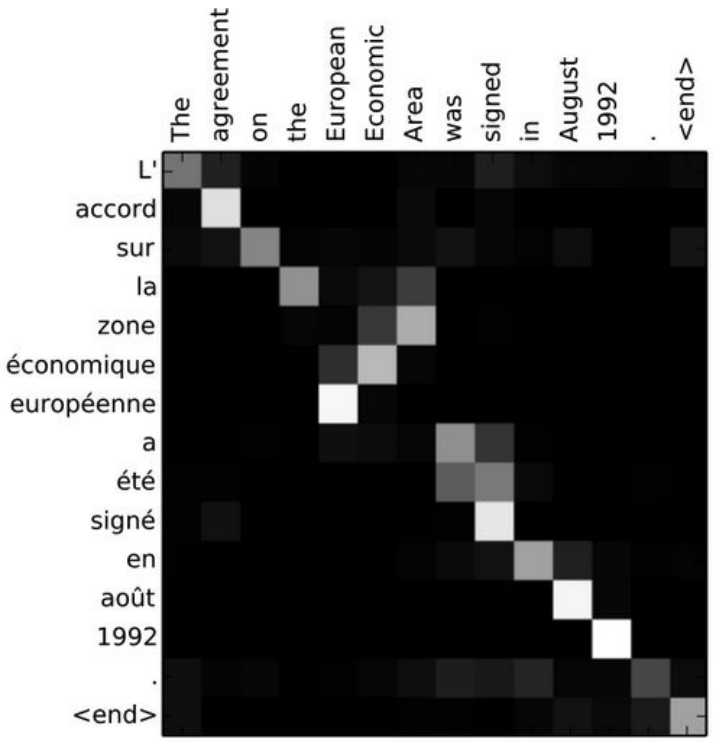
Transformers



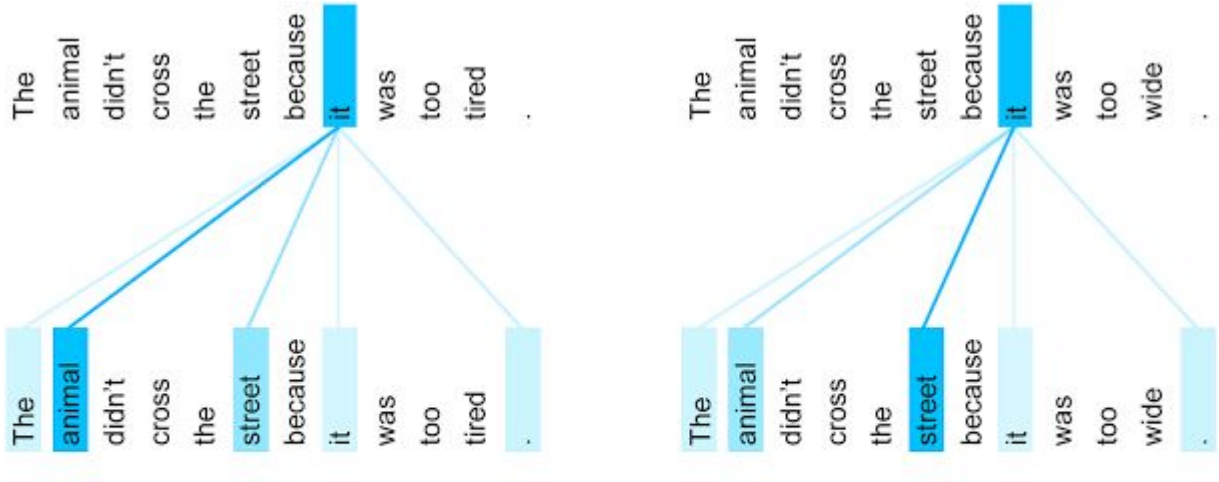
Transformers



Attention

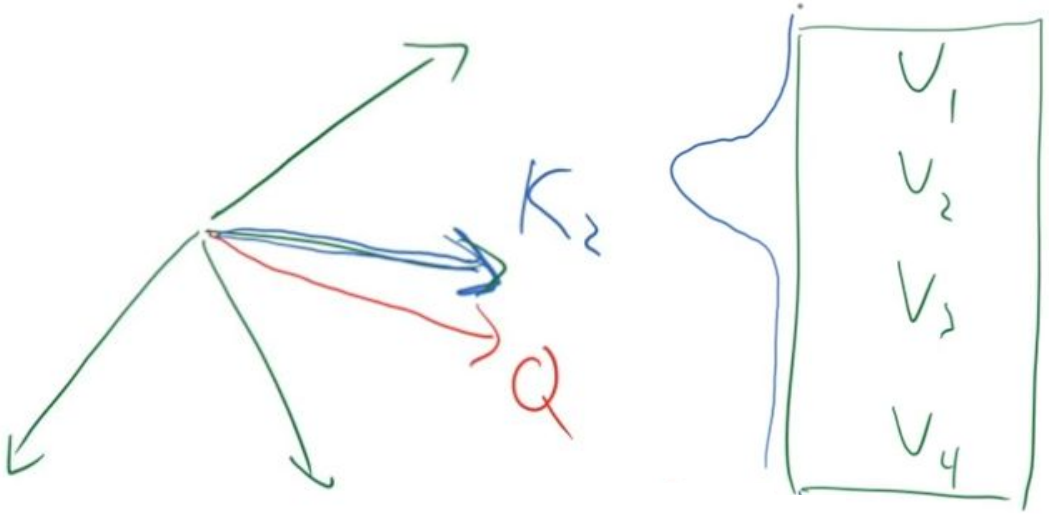

The
agreement
on
the
European
Economic
Area
was
signed
in
August
1992
.
<end>
L'
accord
sur
la
zone
économique
européenne
a
été
signé
en
août
1992
.
<end>

Self-Attention

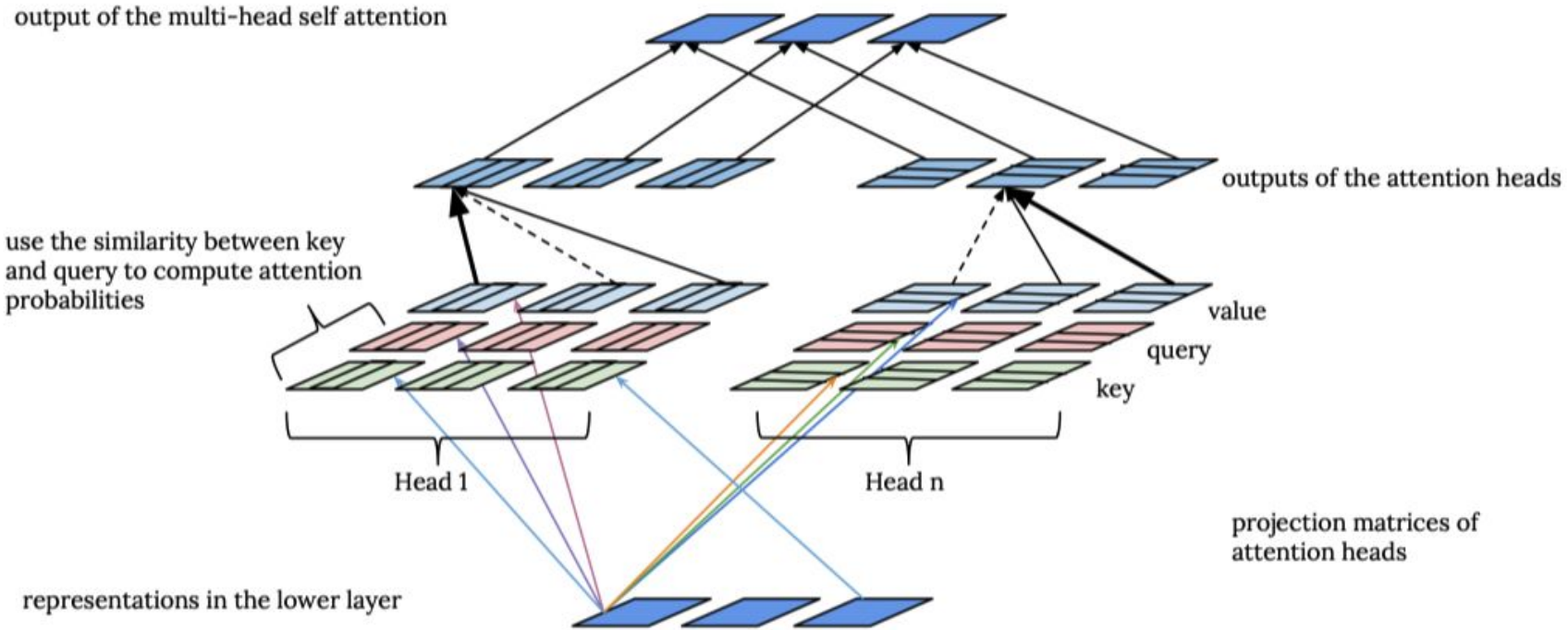


The encoder self-attention distribution for the word "it" from the 5th to the 6th layer of a Transformer trained on English to French translation (one of eight attention heads).

Attention



Multi-Headed Self-Attention



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