

Naive Bayes text classification

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- Likelihood
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Introduction

Artificial Intelligence

Rule-based AI



Long
Yellow
Little bent



Banana

Machine Learning



=

Banana



Long
Yellow
Little bent



Banana

Artificial Intelligence

Rule-based AI



Long
Yellow
Little bent
or
White
Flat
Round

Manually add rule

Banana

Machine Learning



= Banana

Training

Long
Yellow
Little bent
or
White
Flat
Round

Create
own rule

Banana

Example: Starcraft AI

Rule-based AI

- Build Supply Depot
- Build Barrak
- Produce marines
- Build Factory
- ...

AI for
RTS game
is still here!



Machine Learning

- Train AI using millions of replays
- Make its own build order
- Make its own decision in a certain situation



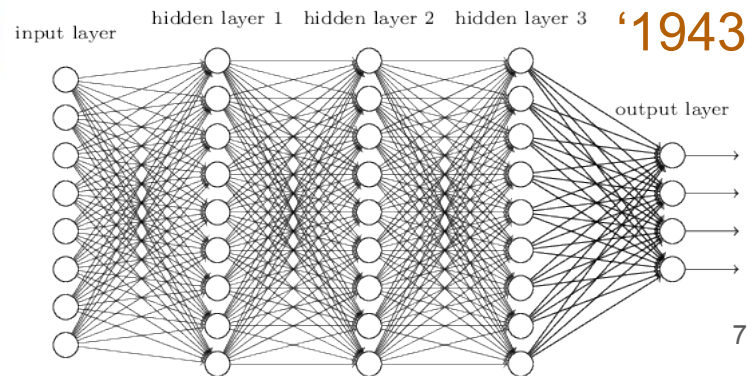
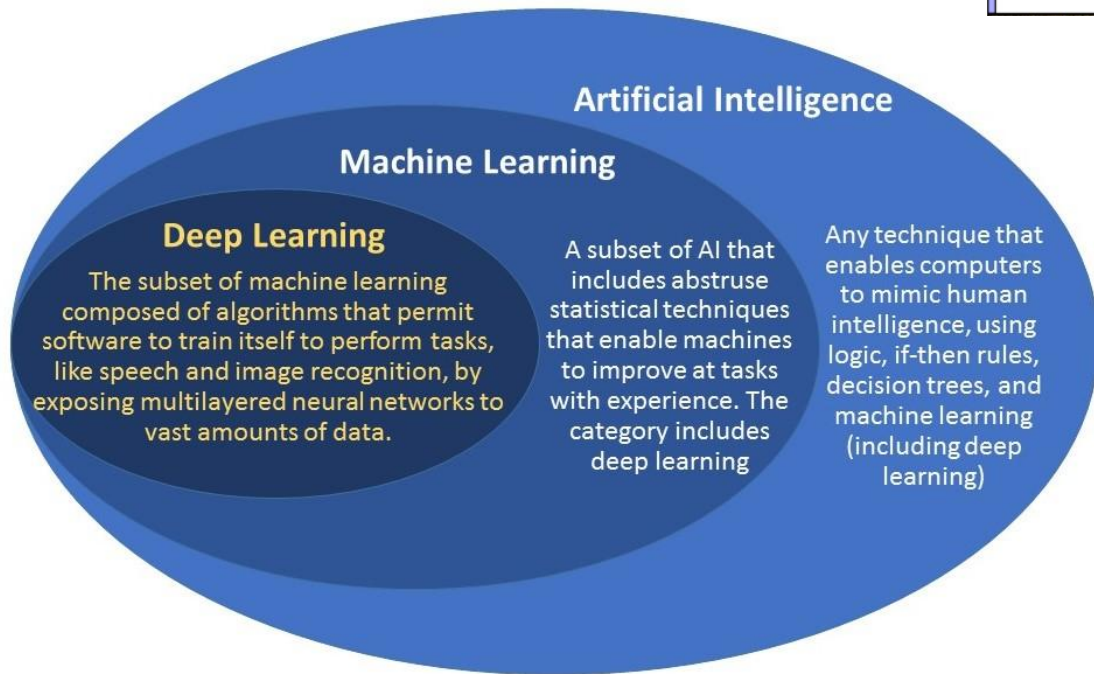
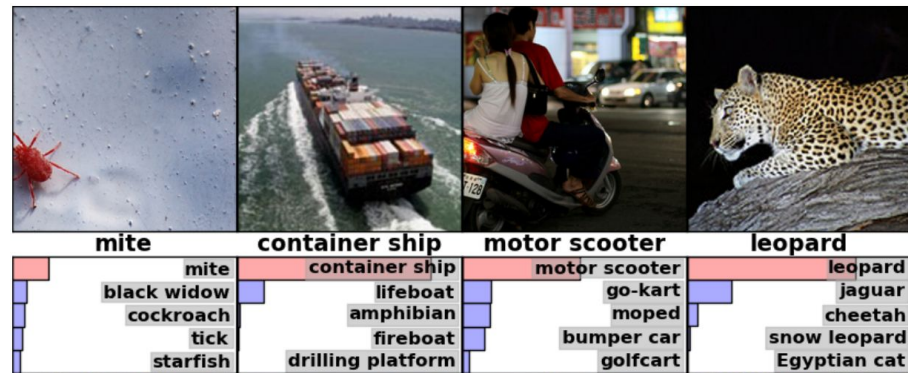
AlphaGo



Humans Are Still Better Than AI at StarCraft—for Now (October, 31th)

<https://www.technologyreview.com/s/609242/humans-are-still-better-than-ai-at-starcraftfor-now/>

Deep Learning (1986~)



Computing power made Deep Learning feasible!



NVIDIA

NVIDIA CORP, M, BATS - O 71.42 H 94.79 L 66.58 C 92.98
Vol (20, false) = 192.41M
BB (20, close, 2) = 40.0603 79.7883 0.3322
BB (20, close, 2) = 40.0603 79.7883 0.3322
MA (200, close) = 16.5002
MA (10, close) = 54.7350
MA (50, close) = 25.9029

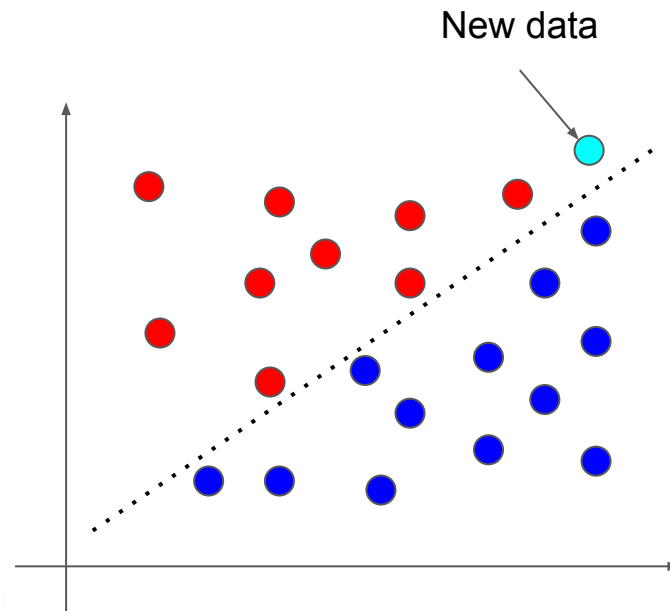
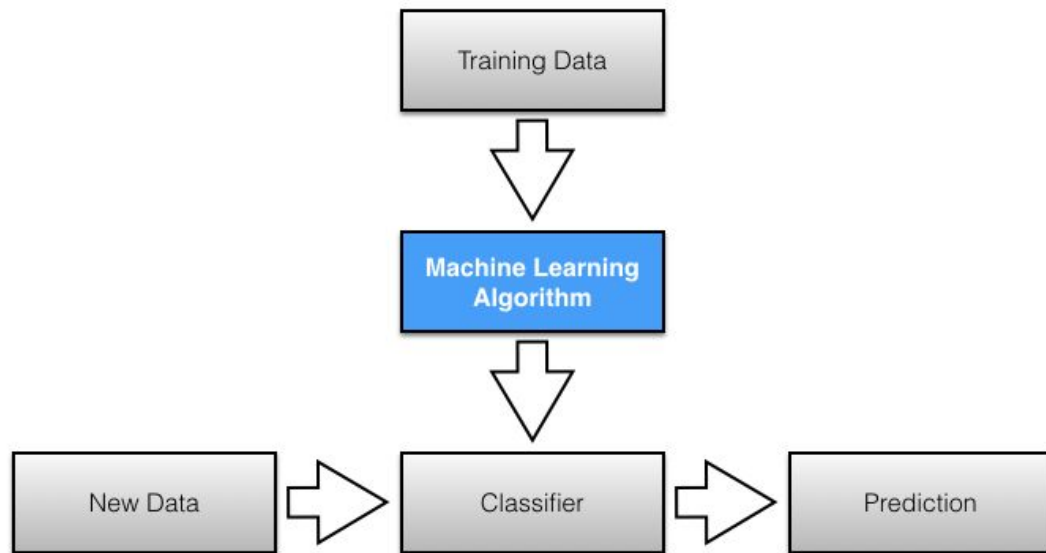
Peak Doub

GFLOPS



Naive Bayes Classification

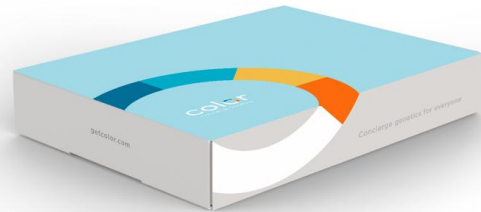
Can a machine make a linear model to categorize new data into trained model?



Bayes' theorem

Breast cancer detection kit

Here's a test kit for breast cancer.



4 out of 1000 women have breast cancer. (prior probability: 0.004)

800 out of **1000 women with breast cancer** will get a positive result.
(sensitivity: 0.8)

100 out of **1000 women without breast cancer** will get a positive result. (false alarm: 0.1)

*If my kit shows positive, what is the **probability** that I actual got cancer?*

Conditional probability

Probability that event A will occur when event X occurred.

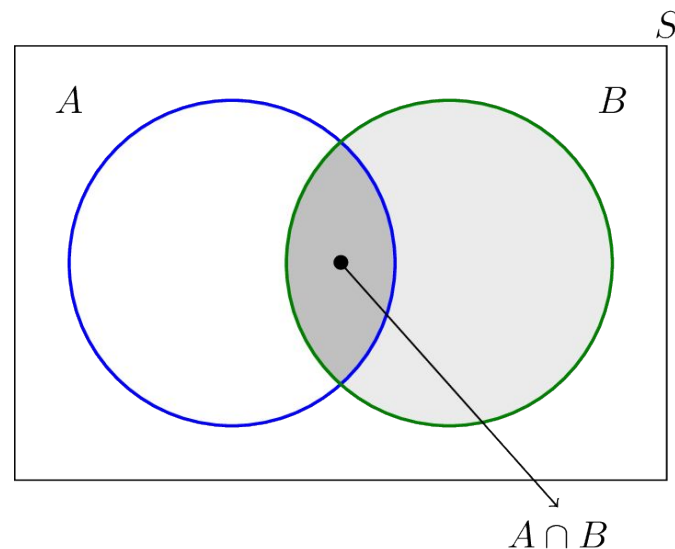
$$P(A|X) = \frac{P(A \cap X)}{P(X)}$$

Example:

A: event that dice showed $n > 3$

X: event that dice showed even number

$$P(A|X) = \frac{P(\{4, 6\})}{P(\{2, 4, 6\})} = \frac{2}{3}$$



$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

Bayes' theorem

Probability that kit shows positive result **when I have cancer**

Probability of having breast cancer

$$P(A|X) = \frac{P(X|A)P(A)}{P(X)}$$

**Real probability that I have cancer
when I have positive kit result.**

Probability that kit shows positive

$P(X|A)$: sensitivity, $P(A)$: prior probability

$$P(X|A) = 0.8$$

: Probability that kit shows positive result when I have cancer

$$P(A) = 0.004$$

: Probability of having breast cancer

P(X): Probability that kit shows positive

$$P(X) = P(X \cap A) + P(X \cap \neg A)$$

$$P(X) = P(X \cap A) + P(X \cap \neg A)$$

$$= \underbrace{P(X|A)}_{0.8} \underbrace{P(A)}_{0.004} + \underbrace{P(X|\neg A)}_{0.1} \underbrace{P(\neg A)}_{0.996} = 0.1028$$

$$P(X|\neg A) = 0.1$$

: Probability that kit shows positive though I don't have cancer.

$$P(\neg A) = 1 - P(A) = 0.996$$

$$P(A|X) = P(X|A) \cdot P(A) / P(X) = 3.11 \%$$

Likelihood

Candy Machine

	Red	Blue	Green
Candy Machine A	2	2	1
Candy Machine B	1	1	1

My kid brought (red, blue, green) = (4, 5, 1) candies for each kind.

**Machine B itself looks more fancy and attractive,
so it has higher probability: $P(B) = 0.6$, $P(A) = 0.4$**

Which candy machine did my kid used?



Definition

$P(X)$ = Probability that my kid bring (5, 6, 1) candy combination.

$P(A)$ = Probability that my kid used machine A

$P(B)$ = Probability that my kid used machine B

$P(A | X)$ = Probability that my kid used machine A when he brought (4, 5, 1)

$P(B | X)$ = Probability that my kid used machine B when he brought (4, 5, 1)

$$P(A|X) = \frac{P(X|A)P(A)}{P(X)} \quad \text{vs.} \quad P(B|X) = \frac{P(X|B)P(B)}{P(X)}$$

We know...

$$P(A|X) : P(B|X) = \frac{P(X|A)P(A)}{P(X)} : \frac{P(X|B)P(B)}{P(X)}$$

**You don't
need to
calculate this**

$$= P(X|A)P(A) : P(X|B)P(B)$$

Likelihood

	Red	Blue	Green
Candy Machine A	2	2	1
Candy Machine B	1	1	1

Probability that I pick up **Red** candy from machine **A**: $2/5$

Probability that I pick up **Blue** candy from machine **A**: $2/5$

Probability that I pick up **Green** candy from machine **A**: $1/5$

Likelihood (cont.)

	Red	Blue	Green
Candy Machine A	2	2	1
Candy Machine B	1	1	1

Probability that I pick up **4 Red** candies from machine **A**: $(2/5)^*(2/5)^*(2/5)^*(2/5)$

Probability that I pick up **5 Blue** candy from machine **A**: $(2/5)^*(2/5)^*(2/5)^*(2/5)^*(2/5)$

Probability that I pick up **1 Green** candy from machine **A**: $(1/5)$

$$P(X | A) = (2/5)^4 * (2/5)^5 * (1/5) = 5.24288e-5$$

Likelihood (cont.)

	Red	Blue	Green
Candy Machine A	2	2	1
Candy Machine B	1	1	1

Probability that I pick up **4 Red** candies from machine **B**: $(1/3)^*(1/3)^*(1/3)^*(1/3)$

Probability that I pick up **5 Blue** candy from machine **B**: $(1/3)^*(1/3)^*(1/3)^*(1/3)^*(1/3)$

Probability that I pick up **1 Green** candy from machine **B**: $(1/3)$

$$P(X | B) = (1/3)^4 * (1/3)^5 * (1/3) = 1.69351e-5$$

Compare!

$$P(A|X) : P(B|X) = \frac{P(X|A)P(A)}{P(X)} : \frac{P(X|B)P(B)}{P(X)}$$

You don't
need to
calculate this

$$= \underset{5.24288\text{e-}5}{P(X|A)} \underset{0.4}{P(A)} : \underset{1.69351\text{e-}5}{P(X|B)} \underset{0.6}{P(B)}$$

$$= 0.67361988 : 0.32638012$$

$$\sim 2 : 1$$

Text Categorization

Finally! we can make text categorization.

Training text (SpongeBob)

Today's the big day, Gary!

Look at me, I'm... ..naked! Gotta be in top physical condition for today, Gary.

I'm ready! I'm ready, I'm ready, I'm ready, I'm ready, I'm ready, I'm ready, I'm ready, I'm ready, I'm ready, I'm ready!

There it is. The finest eating establishment ever established for eating. The Krusty Krab, home of the Krabby Patty. With a 'Help Wanted' sign in the window! For years I've been dreaming of this moment! I'm gonna go in there, march straight to the manager, look 'im straight in the eye, lay it on the line and... I can't do this! Uh, Patrick!

Training text (Mr. Krabs)

Well lad, it looks like you don't even have your sea legs.

Well lad, well give you a test, and if you pass, you'll be on the Krusty Krew! Go out and fetch me... a, uh, hydrodynamic spatula... with, um, port-and-starboard-attachments, and, uh... turbo drive! And don't come back till you get one!

Carry on! We'll never see that lubber again.

That sounded like hatch doors! Do you smell it? That smell. A kind of smelly smell. A smelly smell that smells smelly.

Anchovies.

Stopword list

a	been	get
about	before	getting
after	being	go
again	between	goes
age	but	going
all	by	gone
almost	came	got
also	can	gotte
am	cannot	had
an	come	has
and	could	ha

Make Bag of words

Python dictionary[word]: count

SpongeBob: {'today': 2, '"s": 1, 'big': 1, 'day': 1, 'gary': 2, 'look': 2, '"m": 13, 'naked': 1, 'got': 1, 'ta': 1, 'top': 1, 'physical': 1, 'condition': 1, 'ready': 11, 'finest': 1, 'eating': 2, 'establishment': 1, 'ever': 1, 'established': 1, 'krusty': 1, 'krab': 1, 'home': 1, ... }

Mr. Krabs: {'well': 3, 'lad': 2, 'looks': 1, 'like': 2, "n't": 2, 'even': 1, 'sea': 1, 'legs': 1, 'give': 1, 'test': 1, 'pass': 1, '"ll": 2, 'krusty': 1, 'krew': 1, 'go': 1, 'fetch': 1, 'uh': 2, 'hydrodynamic': 1, 'spatula': 1, 'um': 1, 'port': 1, 'starboard': 1, 'attachments': 1, 'turbo': 1, ... }

```
import nltk
```

```
import re
```

```
#nltk.download() # if you are first time
```

```
special_chars_remover = re.compile("[^w|_]"
```

```
stpwd = nltk.corpus.stopwords.words('english')
```

```
def create_BOW(sentence):
```

```
    bow = {}
```

```
    sentence = remove_special_characters(sentence)
```

```
    sentence = sentence.lower()
```

```
    tokens = nltk.word_tokenize(sentence)
```

```
    for word in tokens:
```

```
        if len(word) < 1 or word in stpwd: continue
```

```
        word = word.lower()
```

```
        bow.setdefault(word, 0)
```

```
        bow[word] += 1
```

```
    return bow
```

```
def remove_special_characters(sentence):
```

```
    return special_chars_remover.sub(' ', sentence)
```

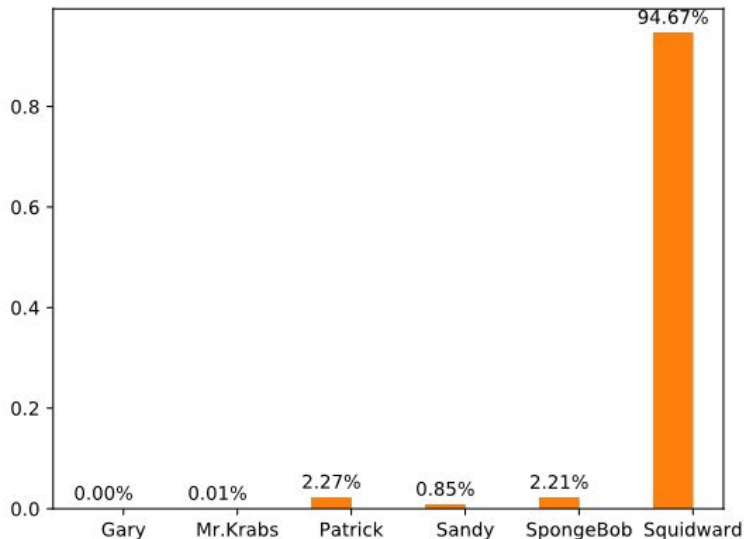
```
sent = input(">>> ")
```

```
print(create_BOW(sent))
```

Run the code!

<https://github.com/SuminHan/NLP-SpongeBob/tree/master/NaiveBayes>

testing_sentence = "I hate this job. I
want to go home and play clarinet"



```
def calculate_doc_prob(training_sentence, testing_sentence, alpha):  
    logprob = 0  
    training_model = create_BOW(training_sentence)  
    testing_model = create_BOW(testing_sentence)  
    """
```

Calculating the probability that training_model may produce testing_model.

We use `math.log`, so note the use.

Ex) $3 * 5 = 15$

$\log(3) + \log(5) = \log(15)$

$5 / 2 = 2.5$

$\log(5) - \log(2) = \log(2.5)$

"""

```
tot = 0
```

```
for word in training_model:
```

```
    tot += training_model[word]
```

```
for word in testing_model:
```

```
    if word in training_model:
```

```
        logprob += math.log(training_model[word])
```

```
        logprob -= math.log(tot)
```

```
    else:
```

```
        logprob += math.log(alpha)
```

```
        logprob -= math.log(tot)
```

```
# log_prob = math.log(prob)
```

```
return logprob
```

← prevent Probability becomes 0

Tips & Reference

Log-likelihood keyness (antconc)

Word List Results 2

Word Types: 3800 Word Tokens: 29947 ^c

Rank	Freq ^a	Word
29	167	formula

Word List Results 1

Word Types: 14202 Word Tokens: 364385 ^d

Rank	Freq ^b	Word
178	294	formula

- Check

AntConc 3.4.4w (Windows) 2014

File Global Settings Tool Preferences Help

Corpus Files

Plankton.txt

Concordance		Concordance Plot	File View	Cluster
Types Before Cut: 3800		Types After Cut:		
Rank	Freq	Keyness	Keyword	
1	132	317.781	karen	
2	167	303.777	formula	

```
>>> def keyness(a, b, c, d):  
...     a = float(a)  
...     b = float(b)  
...     c = float(c)  
...     d = float(d)  
...     E1 = c*(a+b) / (c+d)  
...     E2 = d*(a+b) / (c+d)  
...     ka = (a*math.log(a/E1))  
...     kb = (b*math.log(b/E2))  
...     return 2*(ka+kb)  
...  
>>> keyness(167, 294, 29947, 364385)  
303.7765602866808
```

- Ref: <http://ucrel.lancs.ac.uk/llwizard.html>

Use Python 3.6

Try to Install **PyCharm** (<https://www.jetbrains.com/pycharm/>)



```
C:\> pip install numpy matplotlib nltk
```

(if you need any library to import, just execute on cmd prompt, **windows + R**)

```
C:\> python
```

```
>>> import nltk
```

```
>>> nltk.download()
```

Download NaiveBayes.zip to checkout my example:

⇒ <https://github.com/SuminHan/NLP-SpongeBob/blob/master/NaiveBayes.zip>

Other raw data is on <https://github.com/SuminHan/NLP-SpongeBob>, take a look.

Good luck with your project!

Reference

- [1] Elice: <https://academy.elice.io/courses/214/lectures>
- [2] Naive Bayes: http://sebastianraschka.com/Articles/2014_naive_bayes_1.html
- [3] Intro to TensorFlow (Korean): <https://github.com/golbin/TensorFlow-Tutorials>
- [4] SpongeBob Project: <https://github.com/SuminHan/NLP-SpongeBob>

Elice Lecture

<https://elice.io/>

인공지능/머신러닝 맛보기 - 파이썬

과목 정보

강의

게시판

헬프 센터

학습 현황



31

4주 과정

11월 7일 ~ 12월 4일

화

화 20:00

3 시간 라이브 강의

89명

현재 수강 중

Mail me if you have
question

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