Language Models as Zero-Shot Planners: Extracting Actionable Knowledge for Embodied Agents

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Abstract

Can world knowledge learned by large language models (LLMs) be used to act in interactive environments? In this paper, we investigate the possibility of grounding high-level tasks, expressed in natural language (e.g. "make breakfast"), to a chosen set of actionable steps (e.g. "open fridge"). While prior work focused on learning from explicit step-by-step examples of how to act, we surprisingly find that

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Assign 2, Individual, Feb 28 AoE

Assign1 Marks are yet to be out!

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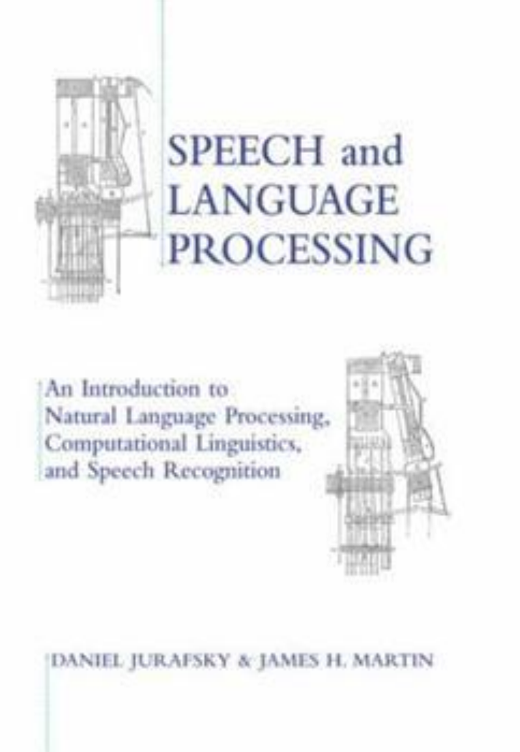
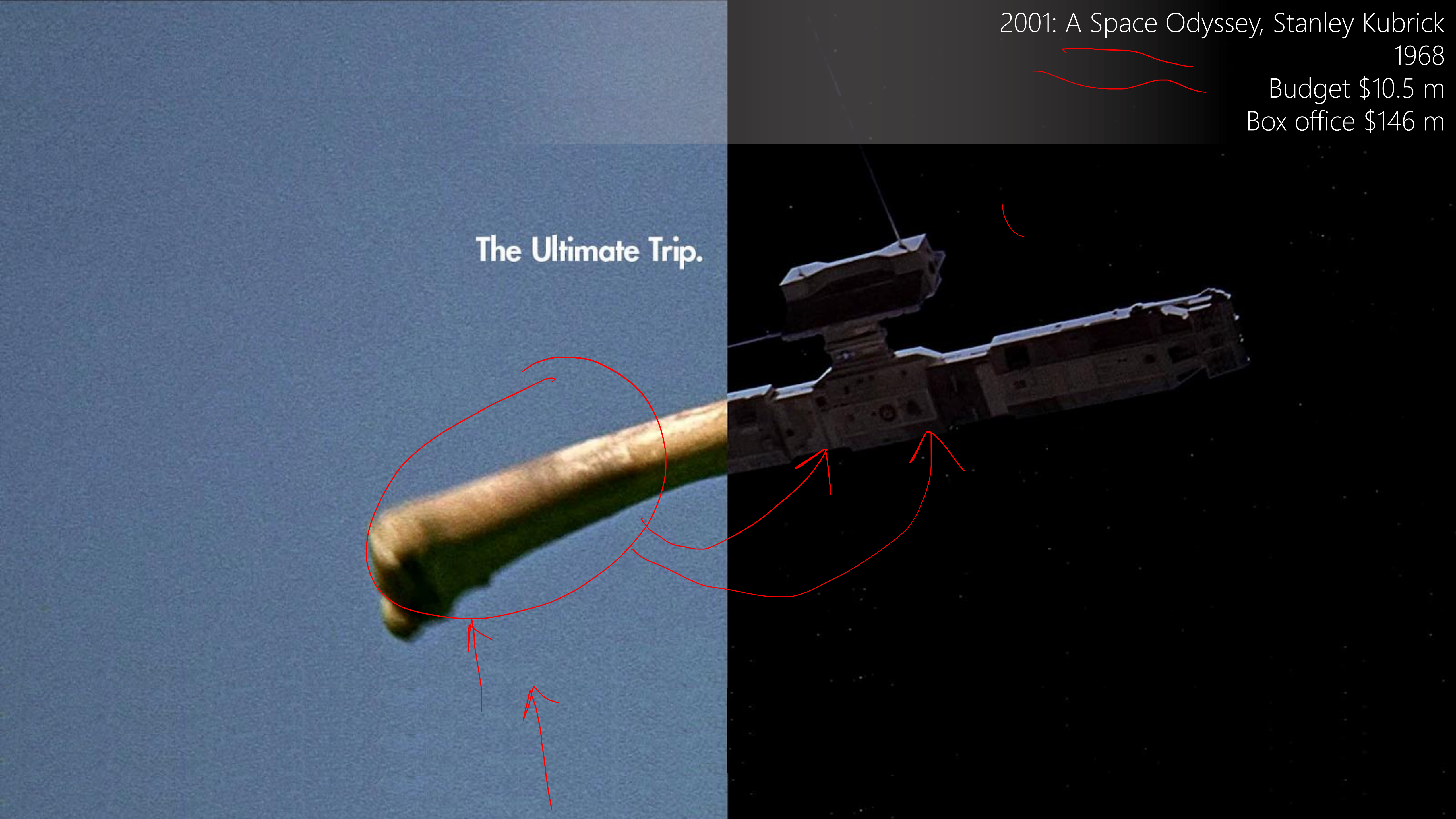
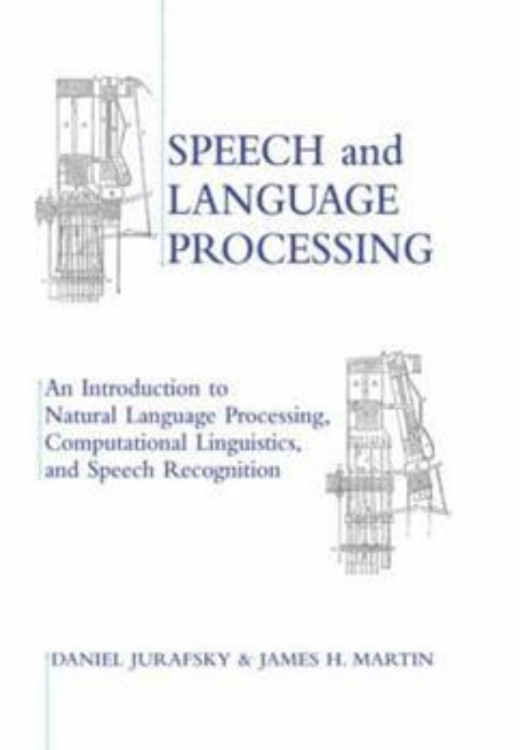


Neural Language Models

CH07

2001: A Space Odyssey, Stanley Kubrick
1968
Budget $10.5 m
Box office $146 m





Naive Bayes and Sentiment Classification

CH04

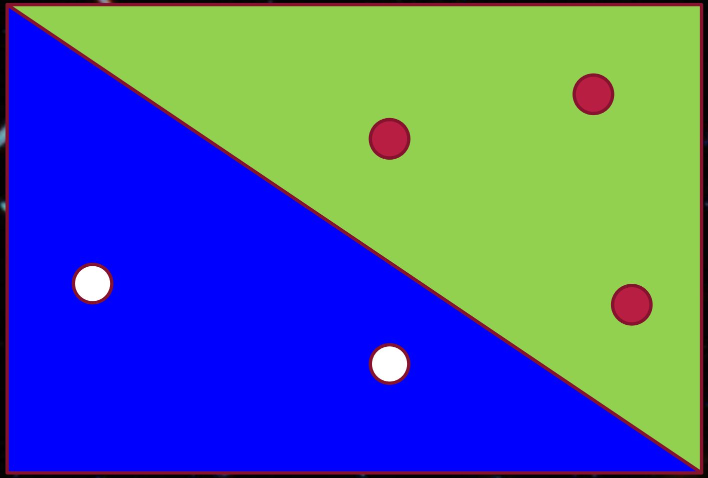
Learning to Classify: Classifier

Learning to Classify: Classifier

Bayesian Classifier
Naïve Bayes
Logistic Regression (Linear)
Neural Network (non-Linear)

Learning to Classify: Boolean Classifiers

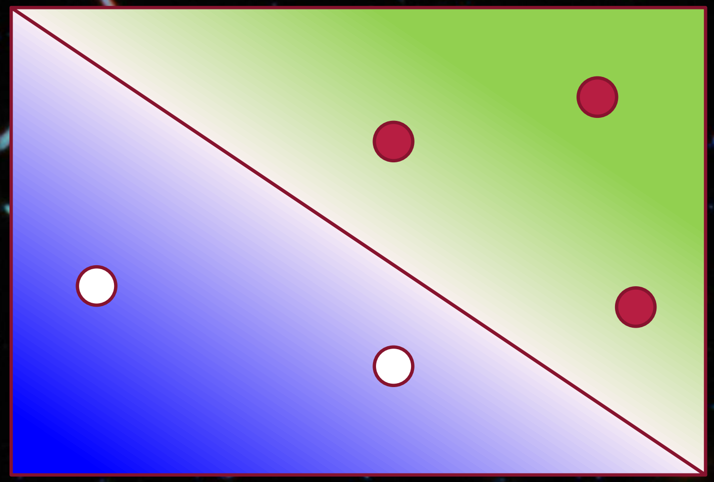
Tokens
Sentences
Documents
Objects
Data Point



$f\colon D \longrightarrow \{0,1\}$: $f(x)$ a Boolean Function

Learning to Classify: Boolean Classifiers

Tokens
Sentences
Documents
Objects
Data Point



$f\colon D \longrightarrow R^{[0,1]}$: $f(x)$ probability value

$f\colon D \longrightarrow R^{[-1,1]}$: $f(x)$ confidence score

Learning to Classify: Boolean Classifiers

Tokens
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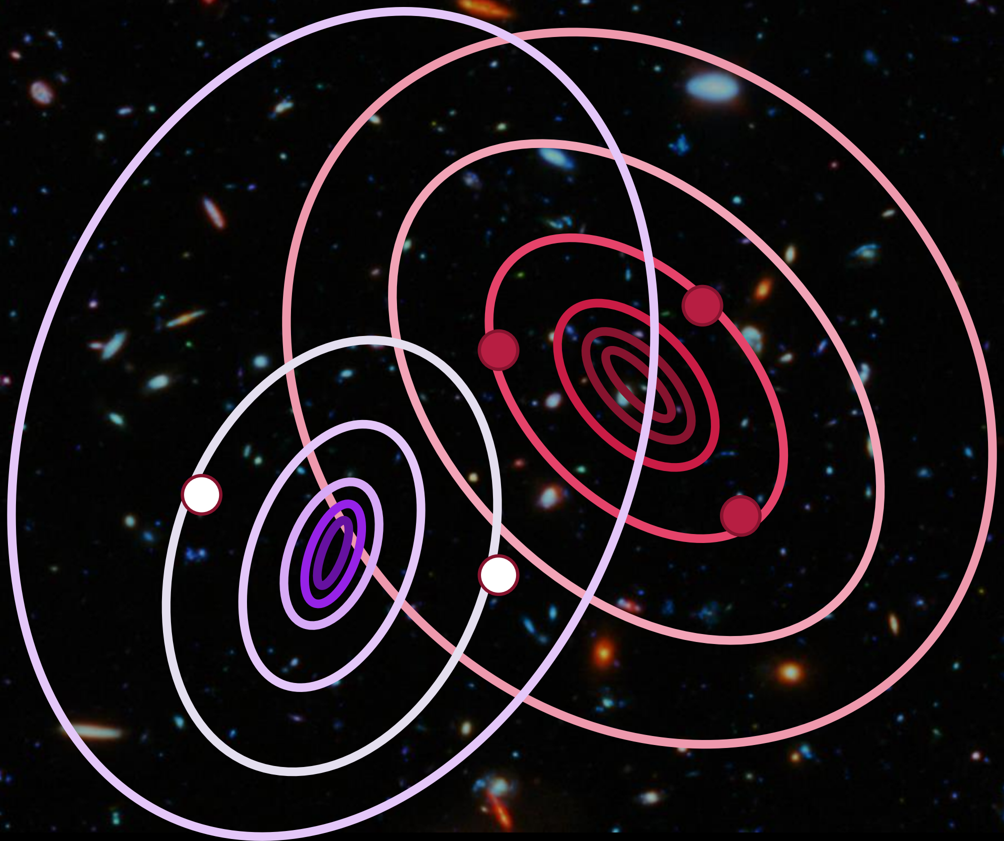


f: D $\rightarrow \{0,1\}^{R[0,1]}$

Mixture or Overlapping Classification

Learning to Classify: Classifier

Bayesian Classifier

Naïve Bayes

Logistic Regression (Linear)

Neural Network (non-Linear)

Bayesian Inference

$$P(H|E) = \frac{P(E|H)P(H)}{P(E)} = \frac{P(E|H)P(H)}{\sum_{H\in\mathcal{H}} P(E|H)\,P(H)}$$

$$E: Event \mid Evidence$$
$$H: Hopothesis$$

Posterior

Evidence → Hypothesis

An event happened. Was it according to my belief?

$$P(H|E) = \frac{P(E|H)P(H)}{P(E)} = \frac{P(E|H)P(H)}{\sum_{H\in\mathcal{H}} P(E|H)\,P(H)}$$

$E: Event \mid Evidence$

$H: Hopothesis$

Prior

P(Hypothesis)

How much your belief is probable regardless of the event (before the event)?

$$P(H|E) = \frac{P(E|H)P(H)}{P(E)} = \frac{P(E|H)P(H)}{\sum_{H\in\mathcal{H}} P(E|H)\,P(H)}$$

$E: Event \mid Evidence$

$H: Hopothesis$

Likelihood!

Hypothesis → Evidence

If I want to build the world according to belief, what events happen?

$$P(H|E) = \frac{P(E|H)P(H)}{P(E)} = \frac{P(E|H)P(H)}{\sum_{H \in \mathcal{H}} P(E|H)\,P(H)}$$

$E: Event \mid Evidence \mid Language$

$H: Hypothesis \mid Model$

Marginal Likelihood!

Normalized over all Hypothesis

The chance that the event happens considering all beliefs

$$P(H|E) = \frac{P(E|H)P(H)}{P(E)} = \frac{P(E|H)P(H)}{\sum_{H \in \mathcal{H}} P(E|H)\, P(H)}$$

$H_0 + H_1$
$H_2 + \ldots$

$$E: Event \mid Evidence$$
$$H: Hopothesis$$

Example

Iran vs. Canada

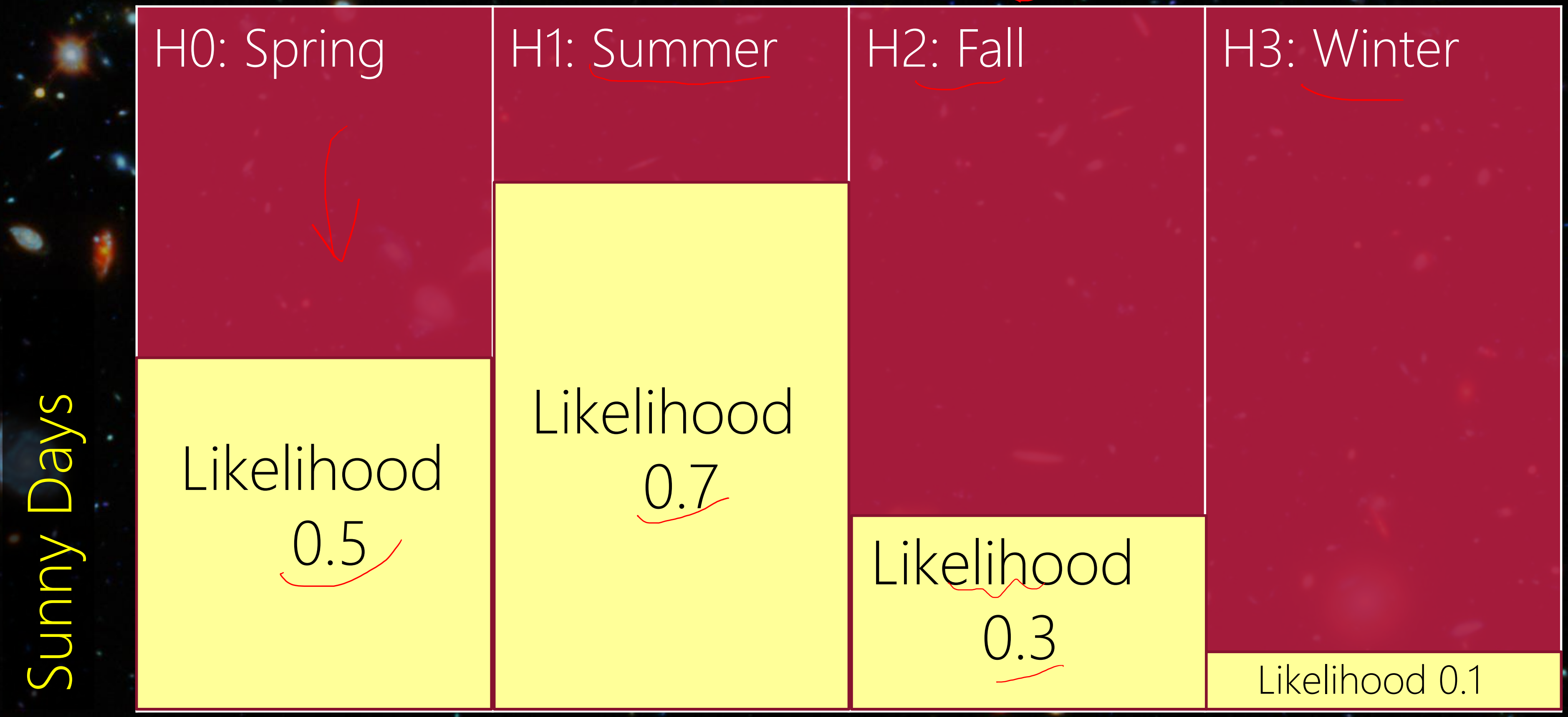
$$P(H|E) = \frac{P(E|H)P(H)}{P(E)} = \frac{P(E|H)P(H)}{\sum_{H\in\mathcal{H}} P(E|H)\,P(H)}$$

$E: Event \mid Evidence$

$H: Hopothesis$

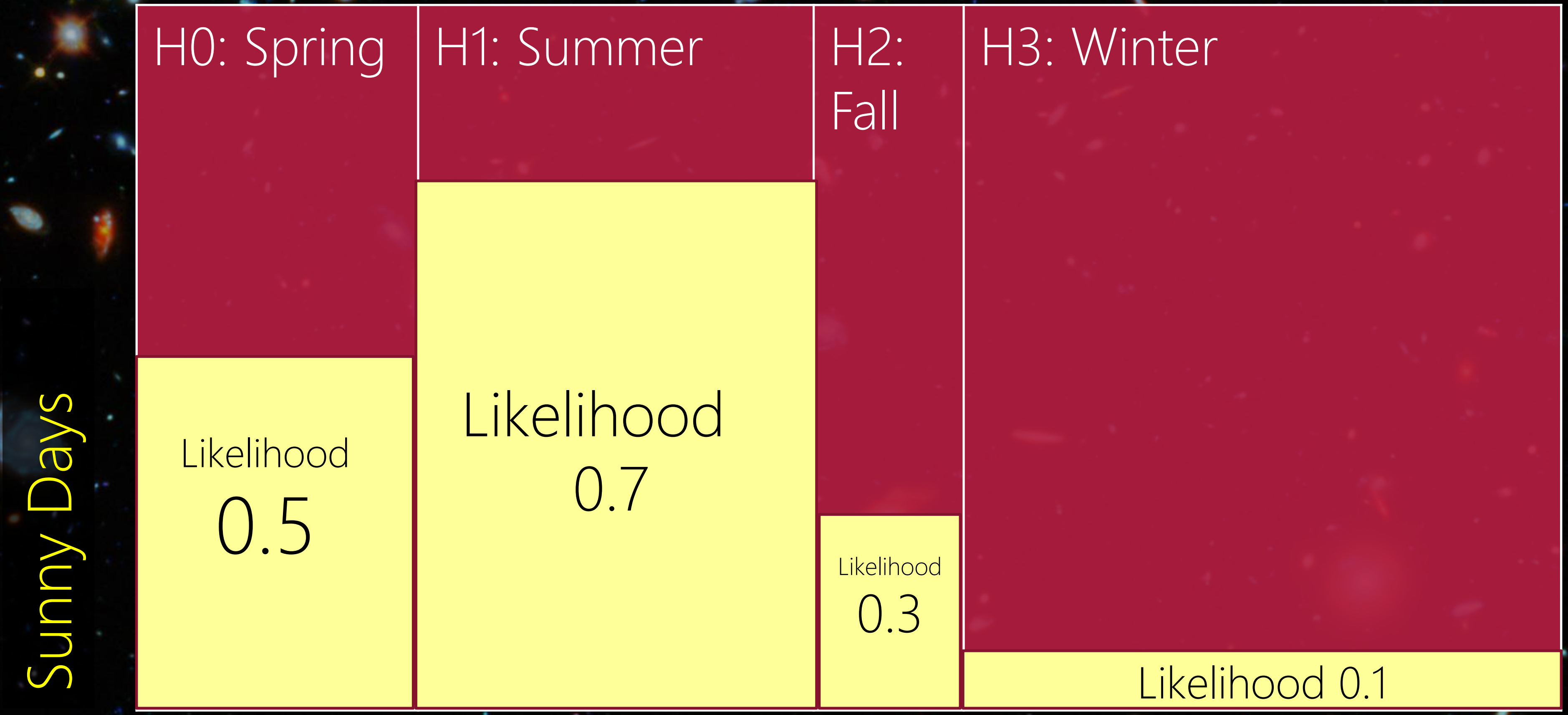
Hypothesis in Iran

Priors = $P(H_i)$ = 1/4



Hypothesis in Canada

Priors = $P(H_i)$ → Not uniform! → $P(H_i)$ = [0.25, 0.3,0.05, 0.4]



Evidence → Hypothesis

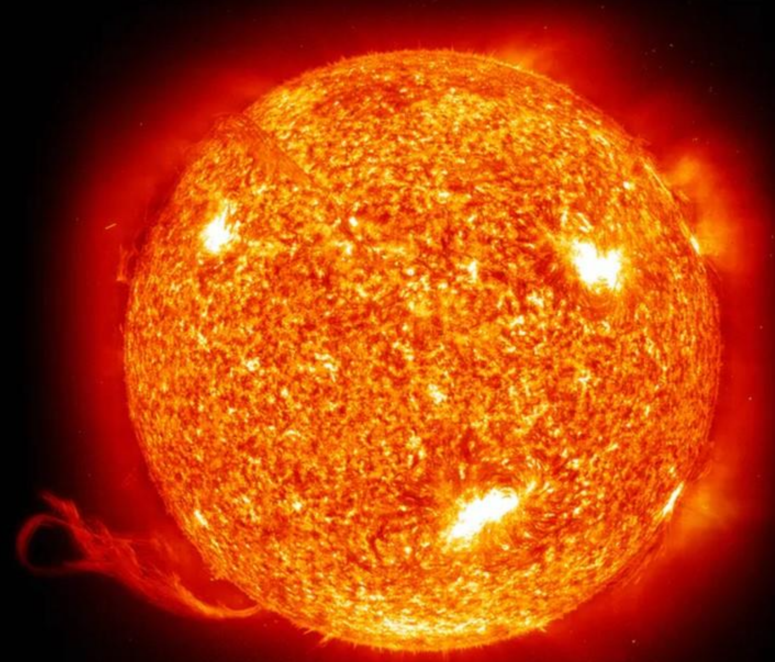
We see a sunny day in Iran! What is the season?

P(Spring | Sunny) = ?

P(Summer | Sunny) =?

P(Fall | Sunny) =?

P(Winter | Sunny) =?



Evidence → Hypothesis

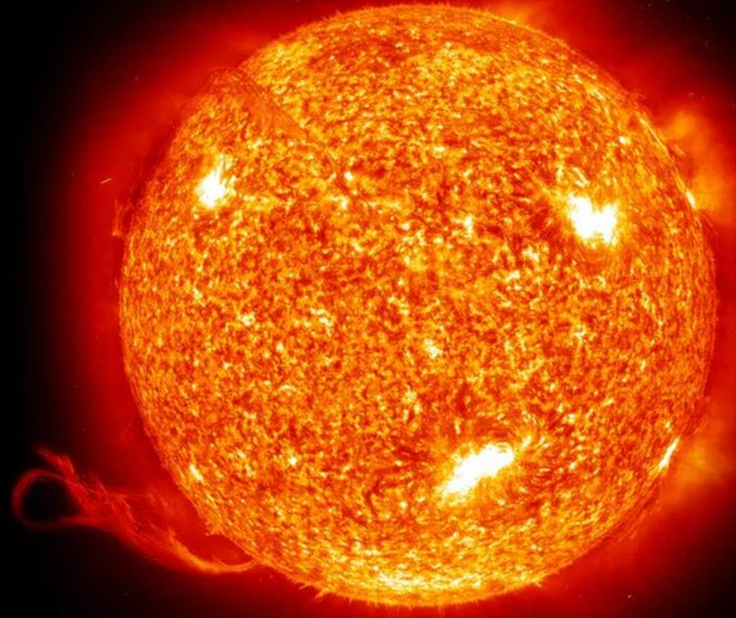
We see a sunny day in Iran! What is the season?

$$P(\text{Spring} \mid \text{Sunny}) = \frac{P(\text{Sunny}|H0)P(H0)}{P(\text{Sunny})} = \frac{P(H0)}{P(\text{Sunny})} \times 0.5$$

$$P(\text{Summer} \mid \text{Sunny}) = \frac{P(\text{Sunny}|H1)P(H1)}{P(\text{Sunny})} = \frac{P(H1)}{P(\text{Sunny})} \times 0.7$$

$$P(\text{Fall} \mid \text{Sunny}) = \frac{P(\text{Sunny}|H2)P(H2)}{P(\text{Sunny})} = \frac{P(H2)}{P(\text{Sunny})} \times 0.3$$

$$P(\text{Winter} \mid \text{Sunny}) = \frac{P(\text{Sunny}|H3)P(H3)}{P(\text{Sunny})} = \frac{P(H3)}{P(\text{Sunny})} \times 0.1$$

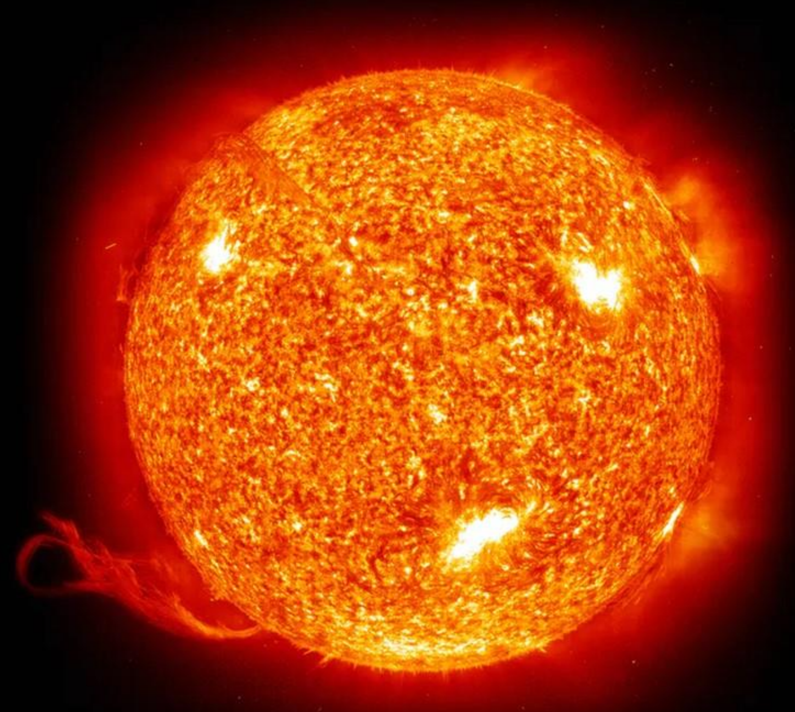


Maximum Posterior: Argmax $P(H_i \mid \text{Sunny})$

Evidence → Hypothesis

We see a sunny day in Canada! What is the season?

P(Spring | Sunny) = ?
P(Summer | Sunny) =?
P(Fall | Sunny) =?
P(Winter | Sunny) =?



Evidence → Hypothesis

We see a sunny day in Canada! What is the season?

$$P(\text{Spring} \mid \text{Sunny}) = \frac{P(\text{Sunny}|H0)P(H0)}{P(\text{Sunny})} = \frac{0.25}{P(\text{Sunny})} \times 0.5$$

$$P(\text{Summer} \mid \text{Sunny}) = \frac{P(\text{Sunny}|H1)P(H1)}{P(\text{Sunny})} = \frac{0.3}{P(\text{Sunny})} \times 0.7$$

$$P(\text{Fall} \mid \text{Sunny}) = \frac{P(\text{Sunny}|H2)P(H2)}{P(\text{Sunny})} = \frac{0.05}{P(\text{Sunny})} \times 0.3$$

$$P(\text{Winter} \mid \text{Sunny}) = \frac{P(\text{Sunny}|H3)P(H3)}{P(\text{Sunny})} = \frac{0.4}{P(\text{Sunny})} \times 0.1$$

We see a sunny day in Canada! What is the season?

$$P(\text{Spring} \mid \text{Sunny}) = \frac{P(\text{Sunny}|H0)P(H0)}{P(\text{Sunny})} = \frac{0.25}{P(\text{Sunny})} \times 0.5$$

$$P(\text{Summer} \mid \text{Sunny}) = \frac{P(\text{Sunny}|H1)P(H1)}{P(\text{Sunny})} = \frac{0.3}{P(\text{Sunny})} \times 0.7$$

$$P(\text{Fall} \mid \text{Sunny}) = \frac{P(\text{Sunny}|H2)P(H2)}{P(\text{Sunny})} = \frac{0.05}{P(\text{Sunny})} \times 0.3$$

$$P(\text{Winter} \mid \text{Sunny}) = \frac{P(\text{Sunny}|H3)P(H3)}{P(\text{Sunny})} = \frac{0.4}{P(\text{Sunny})} \times 0.1$$

Maximum Posterior: Argmax $P(H_i \mid \text{Sunny})$

MAP vs. MLE

Maximum a Posteriori vs. Maximum Likelihood Estimation

/ˌpɒsteriˈɔːraɪ/
/ˌpəʊstɪriˈɔːri/

$$argmax\ P(H|E) = \frac{P(E|H)P(H)}{P(E)} = \frac{P(E|H)P(H)}{\sum_{H\in\mathcal{H}} P(E|H)\,P(H)}$$

$E: Event \mid Evidence$

$H: Hopothesis$

MAP = MLE

Priors are Uniformly Distributed

$$argmax\ P(H|E) = \frac{P(E|H)P(H)}{P(E)} = \frac{P(E|H)P(H)}{\sum_{H \in \mathcal{H}} P(E|H)\,P(H)}$$

$E: Event\ |\ Evidence$

$H: Hopothesis$

MAP ≪ MLE

MAP is more general optimization method!

Priors are not uniform, MLE is weighted by Prior

$$argmax\ P(H|E) = \frac{P(E|H)P(H)}{P(E)} = \frac{P(E|H)P(H)}{\sum_{H\in\mathcal{H}} P(E|H)\,P(H)}$$

$E: Event \mid Evidence$

$H: Hopothesis$

MAP & MLE

Point estimates, i.e., give single real values as probabilities!

0.5 0.2

$$argmax\ P(H|E) = \frac{P(E|H)P(H)}{P(E)} = \frac{P(E|H)P(H)}{\sum_{H \in \mathcal{H}} P(E|H)\,P(H)}$$

$E: Event \mid Evidence$

$H: Hopothesis$

Bayesian Inference

Probability Density Function → MAP → MLE

$$P(a<x<b)=\int_a^b f(x)\,dx$$

x=a

$$\underline{argmax\ P(H|E)} = \frac{P(E|H)P(H)}{P(E)} = \frac{P(E|H)P(H)}{\sum_{H\in\mathcal{H}} P(E|H)\,P(H)}$$

the output is not a single value but a probability density function (when H is a continuous variable) or a probability mass function (when H is a discrete variable).

Learning to Classify: Classifier

Tokens
Sentences
Documents
Objects
Data Point

Events | Evidences

Learning to Classify: Classifier

$$\left.\begin{array}{r}\text{Classes}\\ \text{Labels}\end{array}\right\}\ \text{Hypotheses}$$

Learning to Classify: Classifier

Tokens
Sentences
Documents
Objects
Data Point

} Events | Evidences

E

Classes
Labels

} Hypotheses

H

$$argmax\ P(c|d) = \frac{P(d|c)P(c)}{P(d)} = \frac{P(d|c)P(c)}{\sum_{c\in C} P(d|c)\,P(c)}$$

Document Classification

Sentiment (Review) Analysis (happy, sad, neutral)
Misinformation Analysis (fake-real, reliable-unreliable)
Language Modeling!

Bayes 4 Document Classification

Document (Event) $\longrightarrow$ Classes (Hypothesis)

$$\hat{c} = \underset{c \in C}{argmax} P(c|d) = \underset{c \in C}{argmax} \frac{P(d|c)P(c)}{P(d)} = \underset{c \in C}{argmax} P(d|c)P(c)$$

Bayes 4 Document Classification

Document (Event) $\longrightarrow$ Classes (Hypothesis)

Document (Event): stream of tokens $w_1, w_2, \ldots, w_n$

$$\hat{c} = \underset{c \in C}{argmax}\, P(d|c)P(c)$$

$$= \underset{c \in C}{argmax}\, P(w_1, w_2, \ldots, wn|\, c)\, P(c)$$

Bayes 4 Document Classification

Document (Event) $\longrightarrow$ Classes (Hypothesis)

Document (Event): stream of tokens $w_1, w_2, \ldots, w_n$

$$\hat{c} = \underset{c \in C}{argmax}\, P(d|c)P(c)$$

$$= \underset{c \in C}{argmax}\, P(w_1, w_2, \ldots, wn \,|\, c)\, P(c)$$

$$p(w_1^n) = p(w_1)\, p(w_2|w_1)\, p(w_3|w_2)$$

$$= \underset{c \in C}{argmax} \begin{bmatrix} \text{unigram} \\ \text{bigram} \\ \text{trigram} \end{bmatrix} P(c)$$

$$\ldots$$

Naïve Bayes 4 Document Classification

Document (Event) ⟶ Classes (Hypothesis)

Document (Event): stream of tokens $w_1, w_2, \ldots, w_n$

$$\hat{c} = \underset{c \in C}{argmax}\, P(d|c)P(c)$$

$$= \underset{c \in C}{argmax}\, P(w_1, w_2, \ldots, wn \mid c)\, P(c)$$

$$= \underset{c \in C}{argmax}\, [\text{unigram}]\, P(c)$$

iid

$p(w_1)p(w_2)$

BoW

Naïve Bayes 4 Document Classification

Document (Event) $\longrightarrow$ Classes (Hypothesis)

Document (Event): stream of tokens $w_1, w_2, \ldots, w_n$

$$\hat{c} = \underset{c \in C}{argmax}\, P(d|c)P(c)$$

$$= \underset{c \in C}{argmax}\, P(w_1, w_2, \ldots, wn \mid c)\, P(c)$$

$$= \underset{c \in C}{argmax}\, [\text{unigram}]\, P(c)$$

$$= \underset{c \in C}{argmax} \prod_{i=1}^{n} P(w_i|c)\, P(c)$$

Naïve Bayes 4 Document Classification

Document (Event) ⟶ Classes (Hypothesis)

Document (Event): stream of tokens $w_1, w_2, \ldots, w_n$

$$\hat{c} = \underset{c \in C}{argmax}\, P(d|c)P(c)$$

$$= \underset{c \in C}{argmax}\, P(w_1, w_2, \ldots, wn \,|\, c)\, P(c)$$

$$= \underset{c \in C}{argmax}\, [\text{unigram}]\, P(c)$$

$$= \underset{c \in C}{argmax} \prod_{i=1}^{n} P(w_i|c)\, P(c)$$

$$= \underset{c \in C}{argmax}\, P(c) \prod_{i=1}^{n} P(w_i|c)$$

Naïve Bayes 4 Document Classification

Document (Event) ⟶ Classes (Hypothesis)

Document (Event): stream of tokens $w_1, w_2, \ldots, w_n$

$$\hat{c} = \underset{c \in C}{argmax}\, P(d|c)P(c)$$

$$= \underset{c \in C}{argmax}\, P(w_1, w_2, \ldots, wn \mid c)\, P(c)$$

$$= \underset{c \in C}{argmax}\, [\text{unigram}]\, P(c)$$

$$= \underset{c \in C}{argmax}\, log \textstyle\sum_{i=1}^{n} P(w_i|c)\, P(c)$$

$$= \underset{c \in C}{argmax}\, P(c) log \textstyle\sum_{i=1}^{n} P(w_i|c)$$

Naïve Bayes: Example

	Documents (Sentence)	Sentiment Class (Label)
Train	S_0: just plain boring	Neg (-)
	S_1: entirely predictable and lacks energy	Neg (-)
	S_2: no surprises and very few laughs	Neg (-)
	S_3: very powerful	Pos (+)
	S_4: the most fun film of the summer	Pos (+)
Test	S_5: predictable with no fun	?

Naïve Bayes: Example

	Documents (Sentence)	Sentiment Class (Label)
Train	S_0: just plain boring	Neg (-)
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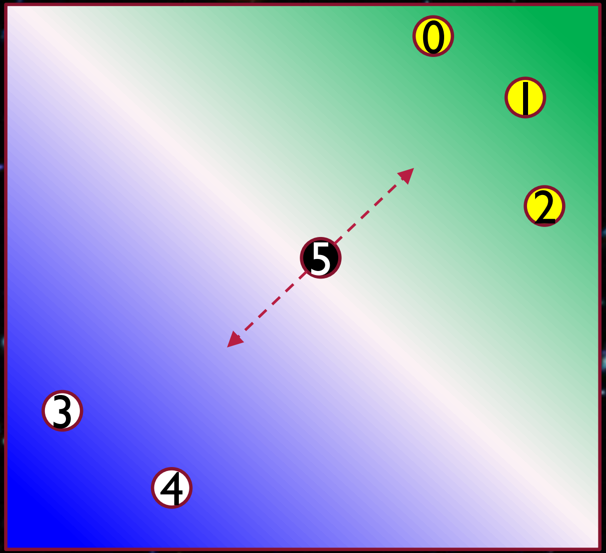
Test	S_5: predictable with no fun	?



$$\hat{c} = \underset{c \in C}{argmax}\, P(S5|c)P(c) = \underset{c \in C}{argmax}\ [\text{unigram}]\ P(c) = \underset{c \in \{+,-\}}{argmax} P(c) \prod_{i=1}^{n} P(w_i|c)$$

Naïve Bayes: Example

	Documents (Sentence)	Sentiment Class (Label)
Train	S_0: just plain boring	Neg (-)
	S_1: entirely predictable and lacks energy	Neg (-)
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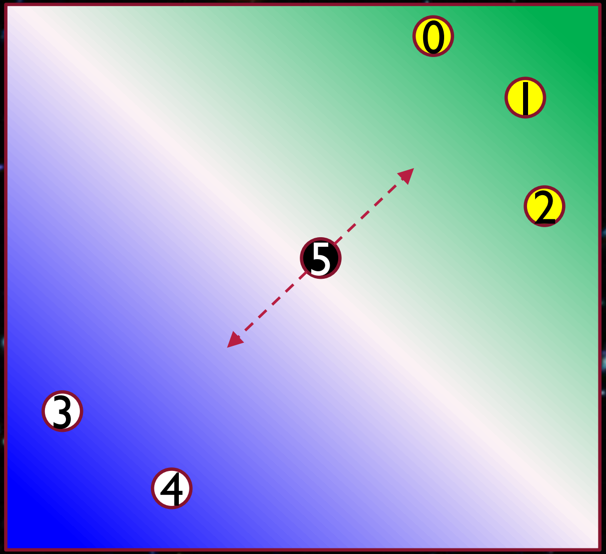
Test	S_5: predictable with no fun	?



$$\hat{c} = \underset{c\in C}{argmax}\, P(S5|c)P(c) = \underset{c\in C}{argmax}\, [\text{unigram}]\, P(c) = \underset{c\in\{+,-\}}{argmax}\, P(c)\prod_{i=1}^{n} P(w_i|c)$$

$$P(-|S5) = P(S5|-)\,P(-) \propto P(-)\,[P(\text{predictable}|-)\,P(\text{with}|-)\,P(\text{no}|-)\,P(\text{fun}|-)] = ?$$

$$P(+|S5) = P(S5|+)\,P(+) \propto P(+)\,[P(\text{predictable}|+)\,P(\text{with}|+)\,P(\text{no}|+)\,P(\text{fun}|+)] = ?$$

Naïve Bayes: Example

	Documents (Sentence)	Sentiment Class (Label)
Train	S_0: just plain boring	Neg (-)
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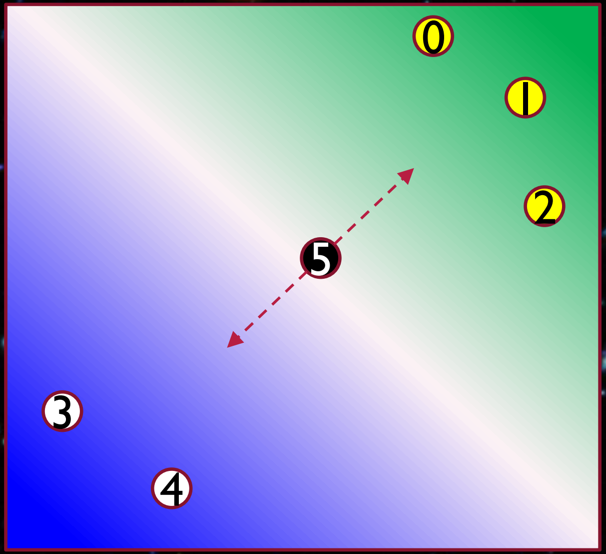

$$\hat{c} = \underset{c \in C}{argmax}\, P(S5|c)P(c) = \underset{c \in C}{argmax}\, [\text{unigram}]\, P(c) = \underset{c \in \{+,-\}}{argmax} P(c) \prod_{i=1}^{n} P(w_i|c)$$

P(−|S5) = P(S5|−) P(−) ∝ P(−) [P(predictable|−) P(with|−) P(no|−) P(fun|−)] = ?
P(+|S5) = P(S5|+) P(+) ∝ P(+) [P(predictable|+) P(with|+) P(no|+) P(fun|+)] = ?

Naïve Bayes: Example

	Documents (Sentence)	Sentiment Class (Label)
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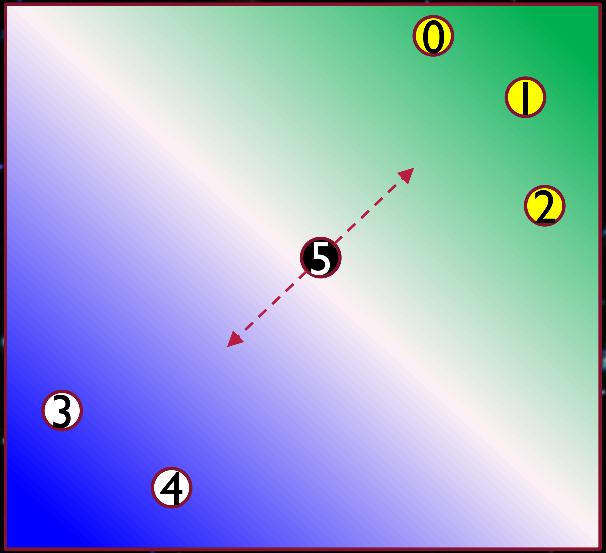

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$$P(-|S5) = P(S5|-)\,P(-) \propto P(-)\,[P(\text{predictable}|-)\,P(\text{with}|-)\,P(\text{no}|-)\,P(\text{fun}|-)] = \frac{3}{5}$$

$$P(+|S5) = P(S5|+)\,P(+) \propto P(+)\,[P(\text{predictable}|+)\,P(\text{with}|+)\,P(\text{no}|+)\,P(\text{fun}|+)] = \frac{2}{5}$$

Naïve Bayes: Example

	Documents (Sentence)	Sentiment Class (Label)
Train	S_0: just plain boring	Neg (-)
	S_1: entirely predictable and lacks energy	Neg (-)
	S_2: no surprises and very few laughs	Neg (-)
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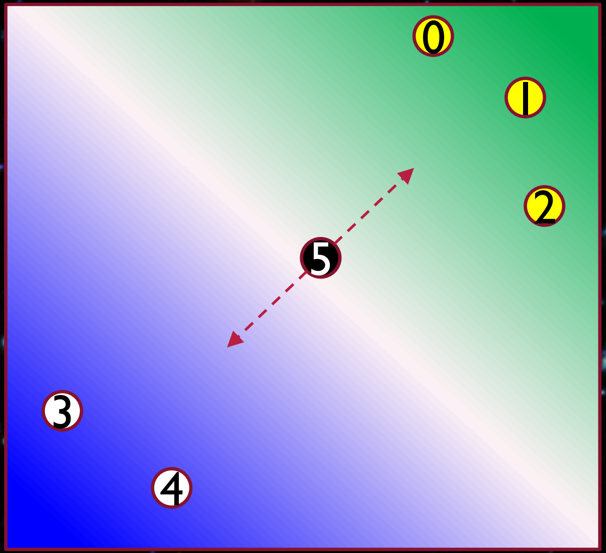
Test	S_5: predictable with no fun	?



$$\hat{c} = \underset{c \in C}{argmax}\, P(S5|c)P(c) = \underset{c \in C}{argmax}\, [\text{unigram}]\, P(c) = \underset{c \in \{+,-\}}{argmax} P(c) \prod_{i=1}^{n} P(w_i|c)$$

$$P(-|S5) = P(S5|-)\, P(-) \propto P(-)\, [P(predictable|-)\, P(with|-)\, P(no|-)\, P(fun|-)] = ?$$

$$P(+|S5) = P(S5|+)\, P(+) \propto P(+)\, [P(predictable|+)\, P(with|+)\, P(no|+)\, P(fun|+)] = ?$$

Naïve Bayes: Example

	Documents (Sentence)	Sentiment Class (Label)
Train	S_0: just plain boring	Neg (-)
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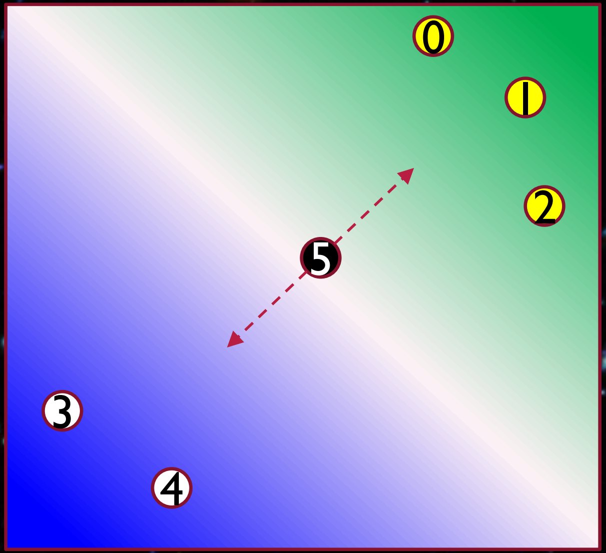


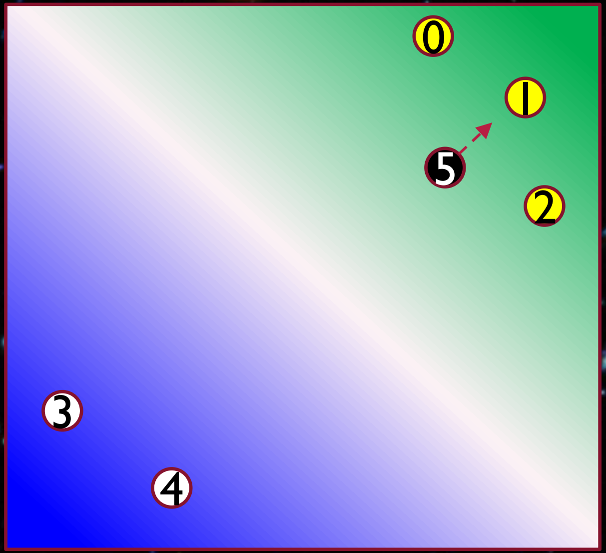
Neg (-) : just plain boring entirely predictable and lacks energy no surprises and very few laughs
Pos (+) : very powerful the most fun film of the summer

$$\text{P(predictable}|-)=\frac{\#preditable}{\#total\ tokens\ in\ (-)}=\frac{1}{14};\ \text{P(with}|-)=\frac{\#with}{\#total\ tokens\ in\ (-)}=\frac{0}{14};\ \text{P(no}|-)=\frac{\#no}{\#total\ tokens\ in\ (-)}=\frac{1}{14};\ \text{P(fun}|-)=\frac{\#fun}{\#total\ tokens\ in\ (-)}=\frac{0}{14}$$

$$\text{P(predictable}|+)=\frac{\#preditable}{\#total\ tokens\ in\ (+)}=\frac{0}{9};\ \text{P(with}|+)=\frac{\#with}{\#total\ tokens\ in\ (+)}=\frac{0}{9};\ \text{P(no}|+)=\frac{\#no}{\#total\ tokens\ in\ (+)}=\frac{0}{9};\ \text{P(fun}|+)=\frac{\#fun}{\#total\ tokens\ in\ (+)}=\frac{1}{9}$$

Naïve Bayes + Smoothing: Example

	Documents (Sentence)	Sentiment Class (Label)
Train	S_0: just plain boring	Neg (-)
	S_1: entirely predictable and lacks energy	Neg (-)
	S_2: no surprises and very few laughs	Neg (-)
	S_3: very powerful	Pos (+)
	S_4: the most fun film of the summer	Pos (+)
Test	S_5: predictable with no fun	Neg (-)



Neg (-) : just plain boring entirely predictable and lacks energy no surprises and very few laughs
Pos (+) : very powerful the most fun film of the summer

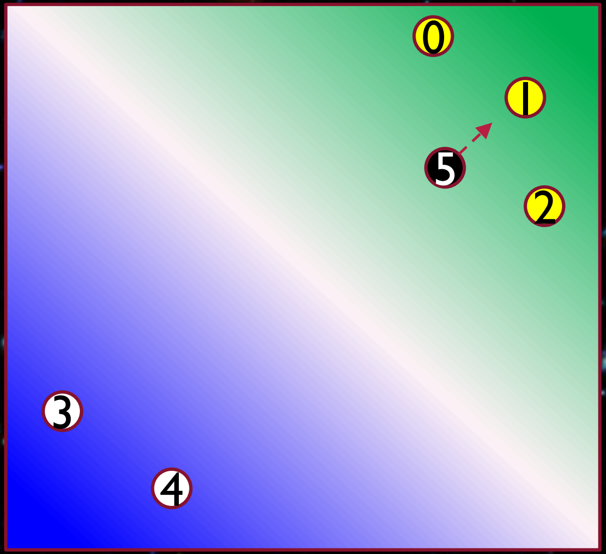
P(predictable|−)= $\frac{\#preditable}{\#total\ tokens\ in\ (-)} = \frac{1+1}{14+23}$; P(with|−)= $\frac{\#with}{\#total\ tokens\ in\ (-)} = \frac{0+1}{14+23}$; P(no|−)= $\frac{\#no}{\#total\ tokens\ in\ (-)} = \frac{1+1}{14+23}$; P(fun|−)= $\frac{\#fun}{\#total\ tokens\ in\ (-)} = \frac{0+1}{14+23}$

P(predictable|+)= $\frac{\#preditable}{\#total\ tokens\ in\ (+)} = \frac{0+1}{9+23}$; P(with|+)= $\frac{\#with}{\#total\ tokens\ in\ (+)} = \frac{0+1}{9+23}$; P(no|+)= $\frac{\#no}{\#total\ tokens\ in\ (+)} = \frac{0+1}{9+23}$; P(fun|+)= $\frac{\#fun}{\#total\ tokens\ in\ (+)} = \frac{1+1}{9+23}$

Naïve Bayes + Smoothing: Example

	Documents (Sentence)	Sentiment Class (Label)
Train	S_0: just plain boring	Neg (-)
	S_1: entirely predictable and lacks energy	Neg (-)
	S_2: no surprises and very few laughs	Neg (-)
	S_3: very powerful	Pos (+)
	S_4: the most fun film of the summer	Pos (+)
Test	S_5: predictable with no fun	Neg (-)

fun and not pred neg



Neg (-) : just plain boring entirely predictable and lacks energy no surprises and very few laughs
Pos (+) : very powerful the most fun film of the summer

$$P(-|S5) = P(S5|-)\,P(-) \propto P(-)\,[P(\text{predictable}|-)\,P(\text{with}|-)\,P(\text{no}|-)\,P(\text{fun}|-)] = \frac{3}{5}\times\frac{2}{37}\times\frac{1}{37}\times\frac{2}{37}\times\frac{1}{37} = 0.00000128057$$

$$P(+|S5) = P(S5|+)\,P(+) \propto P(+)\,[P(\text{predictable}|+)\,P(\text{with}|+)\,P(\text{no}|+)\,P(\text{fun}|+)] = \frac{2}{5}\times\frac{1}{32}\times\frac{1}{32}\times\frac{1}{32}\times\frac{2}{32} = 0.000000762939453$$

Naïve Bayes 4 LM! How?

Naïve Bayes 4 LM

classify the context into the class of next token!

$$P(w_n | w_1, w_2, \ldots, wn_{-1})$$

$|V|$

	Documents (Sentence)	Next Word Class (Label)
Train	S_0: just plain	boring
	S_1: entirely predictable and lacks	energy
	S_2: no surprises and very few	laughs
	S_3: very	powerful
	S_4: the most fun film of the	summer
Test	S_5: predictable with no ░	?

Emotion Analysis & Opinion Mining

Motivation

Online Marketing
Customer Feedback

Age and geographic differences in the levels of happiness!

Dodds and Danforth. Measuring the happiness of large-scale written expression: Songs, blogs, and presidents. Journal of Happiness Studies, 2010

Emotion Analysis & Opinion Mining

Definition

Document → <aspect, opinion, sentiment>

Aspect, Property, Feature, … What

Opinion, Believe, … Why?

Sentiment, Feeling, … How?

Emotion Analysis & Opinion Mining

Example

Document → <aspect, opinion, sentiment>

"*food was great but the service was poor.*" → <food, great, pos>

→ <service, poor, neg>

Sentiment Classification

Example

Document → <~~aspect~~, ~~opinion~~, sentiment>

"food was great but the service was poor." → <Pos>

→ <Neg>

Sentiment Classification

Literature

Lexicon-based: avoids statistical learning altogether!

Classify documents by counting words against positive and negative sentiment word lists(Taboada et al., 2011).

General Inquirer (Stone et al., 1966)
LIWC (Pennebaker et al., 2007)
MPQA Subjectivity Lexicon (Wilson et al., 2005).

E.g., the MPQA has 6885 words: 2718 positive, 4912 negative

+ : admirable, beautiful, confident, dazzling, ecstatic, favor, glee, great
– : awful, bad, bias, catastrophe, cheat, deny, envious, foul, harsh, hate

Sentiment Classification

Literature

Lexicon-based falls short

Irrealis mood (https://en.wikipedia.org/wiki/Irrealis_mood)

"It would be nice if you acted like you understood."

Negation

"That's not bad for the first day."

"This is not the worst thing that can happen."

"Disturbingly good"

Sarcasm & Irony

"That's just what I needed today!"

"Nice perfume. How long did you marinate in it?"

Sentiment Classification

Literature

Machine Learning-based: statistical learning!

Naïve Bayes

Binary Naïve Bayes

Per document, occurrence matters more than frequency

word counts → word occurrence

Sentiment Classification

Literature

Binary Naïve Bayes

Per document, occurrence matters more than frequency

word counts ⟶ word occurrence

Four original documents:

- − it was pathetic the worst part was the boxing scenes
- − no plot twists or great scenes
- + and satire and great plot twists
- + great scenes great film

After per-document binarization:

- − it was pathetic the worst part boxing scenes
- − no plot twists or great scenes
- + and satire great plot twists
- + great scenes film

	NB Counts +	NB Counts −	Binary Counts +	Binary Counts −
and	2	0	1	0
boxing	0	1	0	1
film	1	0	1	0
great	3	1	2	1
it	0	1	0	1
no	0	1	0	1
or	0	1	0	1
part	0	1	0	1
pathetic	0	1	0	1
plot	1	1	1	1
satire	1	0	1	0
scenes	1	2	1	2
the	0	2	0	1
twists	1	1	1	1
was	0	2	0	1
worst	0	1	0	1

Figure 4.3 An example of binarization for the binary naive Bayes algorithm.

Bagging Model for Product Title Quality with Noise

CIKM AnalyticCup 2017

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P R O B L E M

is_clear

"hot sexy red clutch rug sack travel backpack unisex cheap with free gift"

LAZADA
Effortless Shopping

Is_concise

"Hot Sexy Tom Clovers Womens Mens Classy Look Cool Simple Style Casual Canvas Crossbody Messenger Bag Handbag Fashion Bag Tote Handbag Gray"