Data Foundations: Machine Learning Overview and Data Annotation

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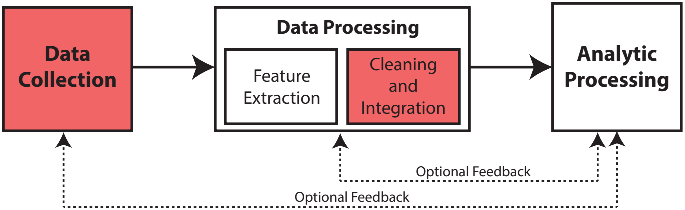
Outline

Data Science Pipeline



- **Learned** the basics of Python
- **Learned** to process many file types (CSV, JSON, XML)
- **Now** we will discuss **machine learning** and **annotating data**

Introduction to ML

Supervised Learning

- abc
- Focus of this class.

Unsupervised Learning

- ABC

Unsupervised Learning

Supervised Learning

Tasks:

- **Classification**
  - Predict a categorical value (e.g., cat/dog given a picture)
- **Regression**
  - Predict a number (e.g., predict stock price)
- **Other** (e.g., Ranking)
  - Example: Google Search
  - Can sometimes be reframed as a classification or regression problem.

Classification

$$h(x) = y$$

$$h(\text{“you have been selected to send 100 dollars!”}) = \text{Spam}$$

Classification

- Let $h(x)$ be the "true" mapping.
- We never know it.
- How do we find the best $\hat{h}(x)$ to approximate it?

- Option 1: **rule-based**
  - If x has characters in unicode point range 0370-03FF: $\hat{h}(x) =$ **greek**
  - spam: black-list-address OR ("dollars AND "have been selected")

  - Accuracy can be high
    - If rules are carefully refined by an expert
  - But building and maintaining these rules is expensive

Classification

- Option 2: Supervised Learning
  - Given training data in $<$**x, y**$>$ pairs, learn $\hat{h}(x)$

Text Classification Problems

task	$\mathbf{x}$	y
language ID	text	$\{$english, mandarin, greek, ...$\}$
spam classification	email	$\{$spam, not spam$\}$
authorship attribution	text	$\{$jk rowling, george r. r. martin, ...$\}$
genre classification	novel	$\{$detective, romance, ...$\}$
sentiment analysis	text	$\{$positive, negative, neutral, mixed$\}$

Sentiment Analysis

- Document-level SA: is the entire text **positive** or **negative** (or both/neither) with respect to an implicit target?

- Movie reviews (Peng et al. 2002, Turney 2002)

Training Data

Positive

"... is a film which still causes real, not figurative, chills to run along my spine, and it is certainly the bravest and most ambitious fruit of Coppola's genius"

Negative

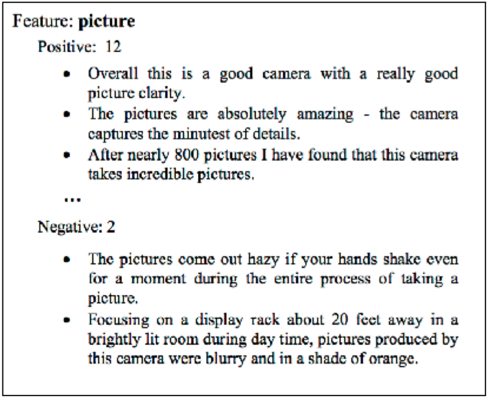
"I hated this movie. Hated hated hated hated hated this movie. Hated it. Hated every simpering stupid vacant audience-insulting moment of it. Hated the sensibility that thought anyone would like it."

Implicit Signal

- Implicit signal: star ratings
- Either treat as an ordinal regression problem ({1, 2, 3, 4, 5} or binarize labels into {pos, neg}

Sentiment Analysis

Is the text positive or negative (or both/neither) with respect to an explicit target **within the text**?


Feature: **picture**

Positive: 12

- Overall this is a good camera with a really good picture clarity.
- The pictures are absolutely amazing - the camera captures the minutest of details.
- After nearly 800 pictures I have found that this camera takes incredible pictures.

...

Negative: 2

- The pictures come out hazy if your hands shake even for a moment during the entire process of taking a picture.
- Focusing on a display rack about 20 feet away in a brightly lit room during day time, pictures produced by this camera were blurry and in a shade of orange.

Sentiment Analysis Downstream Applications

- Political/product opinion mining

Sentiment across time

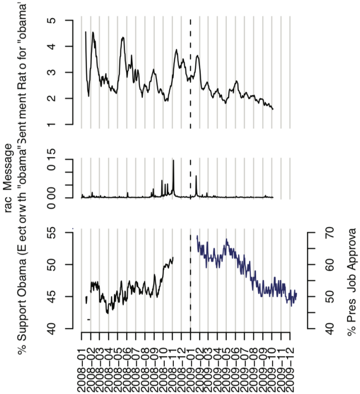


Figure 9: The sentiment ratio for *obama* (15-day window), and fraction of all Twitter messages containing *obama* (day-by-day, no smoothing), compared to election polls (2008) and job approval polls (2009).

O'Connor et al (2010), "From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series"

Sentiment Dictionaries

- MPQA subjectivity lexicon (Wilson et al. 2005) http://mpqa.cs.pitt.edu/lexicons/subj_lexicon/
- LIWC (Linguistic Inquiry and Word Count, Pennebaker 2015)

Positive	Negative
unlimited	lag
prudent	contortions
supurb	fright
closeness	lonely
impeccably	tenuously
fast-paced	plebeian
treat	mortification
destined	outrage
blessing	allegations
steadfastly	disoriented

Why is SA hard?

- Sentiment is a measure of a speaker's private state, which is unobservable
- Sometimes words are a good indicator of sentence sentiment (**love**, **amazing**, **hate**, **terrible**); many times it requires deep word + contextual knowledge

Rodger Ebert, Valentine's Day

"Valentine's Day is being marketed as a Date Movie. I think it's more of a First-Date Movie. If your date **likes** it, do not date that person again. And if you **like** it, there may not be a second date."

Classification

- Supervised Learning
  - Given training data in $<\mathbf{x}, \mathbf{y}>$ pairs, learn $\hat{h}(x)$

$\mathbf{x}$	y
loved it!	positive
terrible movie	negative
not too shabby	positive

$\hat{h}(x)$

- The classification function that we want to learn has two different components
  - the formal structure of the learning method (what's the relationship between the input and output?) $\rightarrow$ **Naive Bayes**, logistic regression, convolutional neural network, etc.
  - the **representation** of the data

Simple Beginnings

But...

Before we can learn the specifics about modeling and coding machine learning tasks, we need to answer the qusstion:

Where does annnotated data come from?

Annotated Data

Modern **data science** is driven by **annotated data**.

- In most cases the data we have is the product of **human judgements**.
  - What is the sentiment of the tweet?
  - What is the object in the picture?
  - What is the topic of the news article?

Issues with human judgement: Ambiguity

- John and Mary are married.

- To each other? or separately?

Issues with human judgement: Ambiguity

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Issues with human judgement: Dogmatism

Dogmatism describes the tendency to lay down opinions as **incontrovertibly true**, without respect for conflicting evidence or the opinions of others.

Which user is more dogmatic in the examples below?

"I'm supposed to trust the opinion of a MS minion? The people that produced Windows ME, Vista and 8? They don't even understand people, yet they think they can predict the behavior of new, selfguiding AI?"
–anonymous

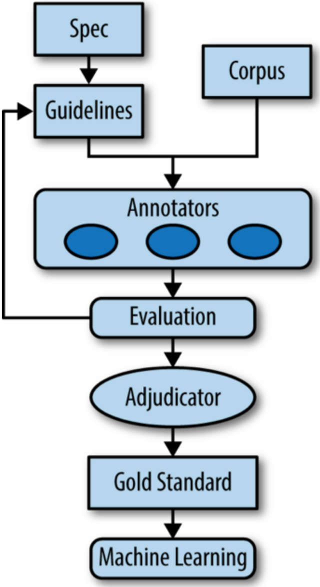
"I think an AI would make it easier for Patients to confide their information because by nature, a robot cannot judge them. Win-win? :D"'
–anonymous

(Fast and Horvitz. 2016)

Issues with human judgement: Sarcasm

"In many respects, you know, they honor President Obama. He's the founder of ISIS. He's the founder of ISIS. He's the founder. He founded ISIS." – Donald Trump

Annotation Pipeline



Pustejovsky and Stubbs (2012), Natural Language Annotation for Machine Learning

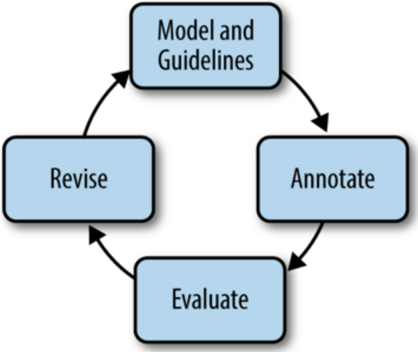
Annotation Process

1. Determine what to annotate.
2. Formalize the instructions for the annotation task
3. Perform a pilot annotation
4. Annotate the data
5. Compute and report inter-annotator agreement, and release the data.

Exercise 1

Complete the Sentiment Annotation Survey on Blackboard

Annotation Pipeline



Pustejovsky and Stubbs (2012), Natural Language Annotation for Machine Learning

Annotation Guidelines

Our goal: Given the constraints of our problem, how can we formalize our descriptions of the annotation process **to encourage multiple annotators to provide the same judgment?**

Annotation Guidelines

- What is the goal of the project?

- What is each class called and how is it used? (Be specific: provide examples and discuss gray areas)

- What **exactly** should be annotated and what should be left alone?

Pustejovsky and Stubbs (2012), Natural Language Annotation for Machine Learning

Example: Sentiment

What best describes the speaker's attitude, evaluation, or judgment towards the [target]? If the whole text is a quote from somebody else (original author) and there is no indication of speaker's attitude, then answer below considering the original author as the speaker.

- **Positive**: there is an explicit or implicit clue in the text suggesting that the speaker's attitude or judgment of the [target] is positive (speaker is appreciative, thankful, excited, optimistic, or inspired by the primary entity)
- **Negative**: there is an explicit or implicit clue in the text suggesting that the speaker's attitude or judgment of the [target] is negative (speaker is critical, angry, disappointed in, pessimistic, expressing sarcasm about, or mocking the primary entity)
- **Mixed**: there is an explicit or implicit clue in the text suggesting that the speaker's attitude or judgment of the [target] is both positive and negative.
- **Unknown**: there is no explicit or implicit clue indicating that the speaker feels positively or negatively.

Mohammad 2016

Practicalities

- Annotation takes time/concentration (can't do it 8 hours a day)

- Annotators get better as they annotate (earlier annotations not as good as later ones)

Why not do it yourself?

- Expensive/time-consuming
- Multiple people provide a measure of consistency: is the task well enough defined?
- Low agreement = not enough training, guidelines not well enough defined, task is bad.

Adjudication

- Adjudication is the process of deciding on a single annotation for a piece of text, using information about the **independent annotations**.
- Can be **time-consuming** (or more so) as primary annotation.
- Does **NOT** need to be identical with the primary annotation. (both annotators can be wrong by chance)

Exercise 2

Judge the annotations in following Data:

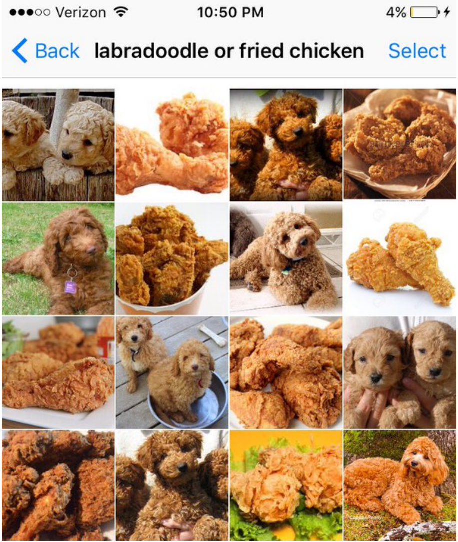
sentiment.txt

You are the judge. Look over the annotations and come up with the following:

- What is your judgment for the correct entity + sentiment annotation?
- How would you amend the annotation guidelines to solicit more consistent annotations?

While judging the annotations, put your judgements in the jupyter notebook file.

Inter-annotator Agreement



https://twitter.com/teenybiscuit/status/705232709220769792/photo/1

Annotator A (x) vs Annotator B (y)

	puppy	fried chicken
puppy	**6**	3
fried chicken	2	**5**

observed agreement $= 11/16 = 68.75\%$

Cohen's Kappa

If classes are imbalanced, we can get high inter-annotator agreement simply chance.

Annotator A (x) vs Annotator B (y)

	puppy	fried chicken
puppy	**7**	4
fried chicken	8	**81**

observed agreement $= p_o = 88/100 = 88\%$

Cohen's Kappa

Expected probability (p_e) of agreement is how often we would expect two annotators to agree assuming **independent** annotations.

$$p_e = P(A = puppy, B = puppy) + P(A = chicken, B = chicken)$$

$$p_e = P(A = puppy)P(B = puppy) + P(A = chicken)P(B = chicken)$$

Cohen's Kappa

$$p_e = P(A = puppy)P(B = puppy) + P(A = chicken)P(B = chicken)$$

P(A = puppy) = 15/100 = 0.15
P(B = puppy) = 11/100 = 0.11
P(A = chicken) = 85/100 = 0.85
P(B = chicken) = 89/100 = 0.89

= 0.15*0.11 + 0.85*0.89
= 0.773

Annotator A (x) vs Annotator B (y)

	puppy	fried chicken
puppy	**7**	4
fried chicken	8	**81**

Cohen's Kappa

If classes are imbalanced, we can get high inter-annotator agreement simply by chance.

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$

$$\kappa = \frac{0.88 - p_e}{1 - p_e}$$

$$\kappa = \frac{0.88 - 0.773}{1 - 0.773}$$

$$= 0.471$$

Annotator A (x) vs Annotator B (y)

	puppy	fried chicken
puppy	**7**	4
fried chicken	8	**81**

$p_o = 88/100 = 0.88\%$

Cohen's Kappa

"Good" values are subject to interpretation, but rule of thumb

Score Range	Interpretation
0.80 - 1.00	Very good agreement
0.60 - 0.80	Good agreement
0.40 - 0.60	Moderate agreement
0.20 - 0.40	Fair agreement
< 0.20	Poor agreement

Example

Annotator A (x) vs Annotator B (y)

	puppy	fried chicken
puppy	**0**	0
fried chicken	0	**100**

Exercise 3

Calculate cohen's kappa using the following numbers:

Annotator A (x) vs Annotator B (y)

	puppy	fried chicken
puppy	**25**	25
fried chicken	25	**25**

Annotator A (x) vs Annotator B (y)

	puppy	fried chicken
puppy	**50**	0
fried chicken	0	**50**

	puppy	fried chicken
puppy	**0**	50
fried chicken	50	**0**

Exercise 4

Write code to calculate and print the cohen's kappa between rater1 and rater2 (the lists below are already in notebook).

rater1 = ['yes','no','yes','yes','yes','yes','no','yes','yes']

rater2 = ['yes','no','no','yes','yes','yes','yes','yes','yes']

Hint: You will need to create the confusion matrix (matrix of how many times each rater agrees for each item). This can be represented as 4 variables

Issues with Cohen's Kappa

- Cohen's kappa can be used for any number of classes.
- Still requires **two** annotators who evaluate the same items.
- Fleiss' kappa generalizes to **multiple** annotators, each of whom may evaluate **different** items (e.g., crowdsourcing)

Fleiss' kappa

- Same fundamental idea of measuring the observed agreement compared to the agreement we would expect by chance.

$$\kappa = \frac{P_o - P_e}{1 - P_e}$$

- With N $>$ 2, we calculate agreement among **pairs** of annotators.

Fleiss' Kappa

n_{ij} is the number of annotators that agree on assigning the i-th class to the j-th item.

o is the total number of annotators

K is the number of classes

For item i with n annotations, how many annotators agree, among all n(n-1) possible pairs.

$$P_i = \frac{1}{o(o-1)} \sum_{j=1}^{K} n_{ij}(n_{ij} - 1)$$

Fleiss' Kappa

[redacted]	Positive	Negative	Neutral	P_i
Tweet 1	3	1	6	**0.4**
Tweet 2	9	1	0	
Tweet 3	3	5	2	
Tweet 4	2	0	8	
p_j				[redacted]

$$P_1 = \frac{1}{10(10-1)} * (3*2 + 1*0 + 6*5) = \mathbf{0.4}$$

Fleiss' Kappa

[redacted]	Positive	Negative	Neutral	P_i
Tweet 1	3	1	6	0.4
Tweet 2	9	1	0	0.8
Tweet 3	3	5	2	0.3111
Tweet 4	2	0	8	**0.6444**
p_j				[redacted]

$$P_4 = \frac{1}{10(10-1)} * (2 * 1 + 0 * -1 + 8 * 7) = \mathbf{0.6444}$$

Fleiss' Kappa

[redacted]	Positive	Negative	Neutral	P_i
Tweet 1	3	1	6	0.4
Tweet 2	9	1	0	0.8
Tweet 3	3	5	2	0.3111
Tweet 4	2	0	8	0.6444
p_j				[redacted]

N is the total number of items (Total Tweets in this example)

Average observed agreement among all items

$$P_o = \frac{1}{N}\sum_{i=1}^{N} P_i = \frac{1}{4} * (0.4 + 0.8 + 0.3111 + 0.6444) = 0.5388$$

Fleiss' Kappa

[redacted]	Positive	Negative	Neutral	P_i
Tweet 1	3	1	6	0.4
Tweet 2	9	1	0	0.8
Tweet 3	3	5	2	0.3111
Tweet 4	2	0	8	0.6444
p_j	**0.425**			[redacted]

N is the total number of items (Total Tweets in this example)
o is the total number of annotators
Probability of category j

$$p_j = \frac{1}{N * o} \sum_{i=1}^{N} n_{ij}$$

$$p_{positive} = \frac{1}{4 * 10} * (3 + 0 + 3 + 2) = \mathbf{0.425}$$

Fleiss' Kappa

[redacted]	Positive	Negative	Neutral	P_i
Tweet 1	3	1	6	0.4
Tweet 2	9	1	0	0.8
Tweet 3	3	5	2	0.3111
Tweet 4	2	0	8	0.6444
p_j	0.425	0.175	**0.4**	[redacted]

N is the total number of items (Total Tweets in this example)
o is the total number of annotators
Probability of category j

$$p_j = \frac{1}{N * o} \sum_{i=1}^{N} n_{ij}$$

$$p_{neutral} = \frac{1}{4 * 10} * (6 + 0 + 2 + 8) = \mathbf{0.4}$$

Fleiss' Kappa

[redacted]	Positive	Negative	Neutral	P_i
Tweet 1	3	1	6	0.4
Tweet 2	9	1	0	0.8
Tweet 3	3	5	2	0.3111
Tweet 4	2	0	8	0.6444
p_j	0.425	0.175	0.4	[redacted]

Expected agreement by chance – joint probability two raters pick the same label is the product of their independent probabilities of picking that label
K is the number of classes

$$P_e = \sum_{j=1}^{K} p_j * p_j = 0.425 * 0.425 + 0.175 * 0.175 + 0.4 * 0.4 = \mathbf{0.3715}$$

Fleiss' kappa

- Same fundamental idea of measuring the observed agreement compared to the agreement we would expect by chance.

$$\kappa = \frac{P_o - P_e}{1 - P_e} = \frac{0.5388 - 0.3715}{1 - 0.3715} = \mathbf{0.2662}$$

Fleiss' Kappa

"Good" values are subject to interpretation, but rule of thumb

Score Range	Interpretation
0.81 - 1.00	Almost Perfect
0.61 - 0.80	Substantial agreement
0.41 - 0.60	Moderate agreement
0.21 - 0.40	Fair agreement
0.01 - 0.20	Slight agreement
< 0.0	Poor agreement

What about Ordinal/Regression Problems?

There are many agreement statistics. Find relevant research on the topic you are working on, then choose the staistic that is generally used.

- Krippendorff's alpha
- Pearson's r
- Kendalls' τ
- Spearmans's ρ

The End

The End