CS388: Natural Language Processing

Lecture 2: Binary Classification

credit: Machine Learning Memes on Facebook

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Administrivia

- Recordings on Canvas
- My OHs started this morning, Anisha and I will hold OHs next week
- P1 due in 12 days

This Lecture

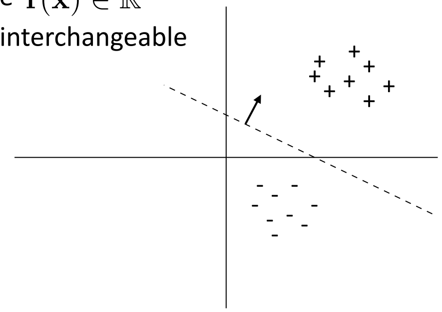
- Linear binary classification fundamentals
- Feature extraction
- Logistic regression
- Perceptron/SVM
- Optimization
- Sentiment analysis

Linear Binary Classification

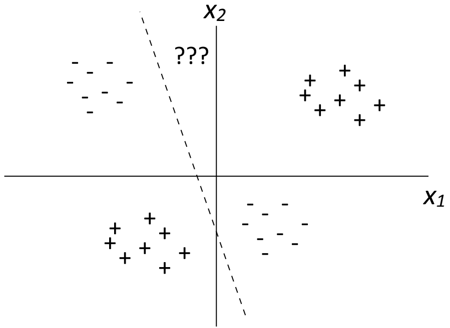
Classification

- Datapoint $\mathbf{x}$ with label $y \in \{0, 1\}$
- Embed datapoint in a feature space $\mathbf{f}(\mathbf{x}) \in \mathbb{R}^n$ but in this lecture $\mathbf{f}(\mathbf{x})$ and $\mathbf{x}$ are interchangeable
- Linear decision rule: $\mathbf{w}^\top \mathbf{f}(\mathbf{x}) > 0$

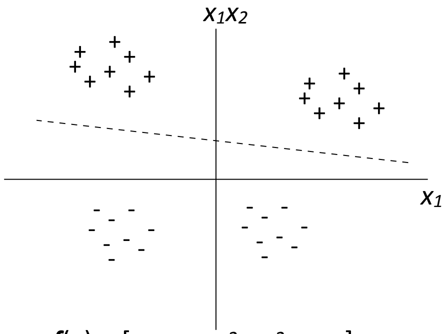
  (No bias term *b* — we have lots of features and it isn't needed)



Linear functions are powerful!



***f*(*x*)** = [x_1, x_2]



***f*(*x*)** = [x_1, x_2, x_1^2, x_2^2, x_1x_2]

- "Kernel trick" does this for "free," but is too expensive to use; with *n* examples training is $O(n^2)$ instead of $O(n \cdot (\text{num feats}))$

Classification: Sentiment Analysis

this movie was great! would watch again Positive

that film was awful, I'll never watch again Negative

- Surface cues can basically tell you what's going on here: presence or absence of certain words (*great*, *awful*)
- Steps to classification:
  - Turn examples like this into feature vectors
  - Pick a model / learning algorithm
  - Train weights on data to get our classifier

Feature Extraction

Feature Representation

this movie was great! would watch again Positive

- Convert this example to a vector using *bag-of-words features*

	[contains *the*]	[contains *a*]	[contains *was*]	[contains *movie*]	[contains *film*]	…
	position 0	position 1	position 2	position 3	position 4	
$\boldsymbol{f}(\boldsymbol{x})$ =	[0	0	1	1	0	…

- Very large vector space (size of vocabulary), sparse features (how many per example?)

Feature Representation

- What are some preprocessing operations we might want to do before we map to words?

Feature Extraction Details

- Tokenization:

  “I thought it wasn’t that great!” critics complained.

  “ I thought it was n’t that great ! ” critics complained .

  - Split out punctuation, contractions; handle hyphenated compounds
- Lowercasing (maybe)
- Filtering stopwords (maybe)
- Buildings the feature vector requires *indexing* the features (mapping them to axes). Store an invertible map from string -> index
  - [contains “the”] is a single feature — put this whole bracketed thing into the indexer to give it a position in the feature space

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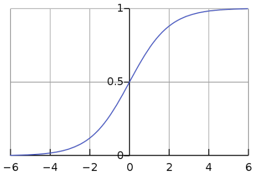
Logistic Regression

Logistic Regression

$$P(y=+|x) = \text{logistic}(w^\top x)$$

$$P(y=+|x) = \frac{\exp(\sum_{i=1}^n w_i x_i)}{1+\exp(\sum_{i=1}^n w_i x_i)}$$



- To learn weights: maximize discriminative log likelihood of data (log P(y|x))

$$\mathcal{L}(\{x_j, y_j\}_{j=1,\ldots,n}) = \sum_j \log P(y_j|x_j)$$ corpus-level LL

$$\mathcal{L}(x_j, y_j=+) = \log P(y_j=+|x_j)$$ one (positive) example LL

$$= \sum_{i=1}^n w_i x_{ji} - \log\left(1+\exp\left(\sum_{i=1}^n w_i x_{ji}\right)\right)$$

sum over features

Logistic Regression

$$\mathcal{L}(x_j, y_j=+) = \log P(y_j=+|x_j) = \boxed{\sum_{i=1}^n w_i x_{ji}} - \log\left(1+\exp\left(\sum_{i=1}^n w_i x_{ji}\right)\right)$$

$$\frac{\partial \mathcal{L}(x_j,y_j)}{\partial w_i} = \boxed{x_{ji}} - \frac{\partial}{\partial w_i}\log\left(\boxed{1+\exp\left(\sum_{i=1}^n w_i x_{ji}\right)}\right)$$

$$= x_{ji} - \frac{1}{\boxed{1+\exp\left(\sum_{i=1}^n w_i x_{ji}\right)}}\frac{\partial}{\partial w_i}\left(\boxed{1+\exp\left(\sum_{i=1}^n w_i x_{ji}\right)}\right)$$ deriv of log

$$= x_{ji} - \frac{1}{1+\exp\left(\sum_{i=1}^n w_i x_{ji}\right)} x_{ji}\exp\left(\sum_{i=1}^n w_i x_{ji}\right)$$ deriv of exp

$$= x_{ji} - x_{ji}\frac{\exp\left(\sum_{i=1}^n w_i x_{ji}\right)}{1+\exp\left(\sum_{i=1}^n w_i x_{ji}\right)} = x_{ji}(1-P(y_j=+|x_j))$$

Logistic Regression

- Update for ***w*** on positive example $= \mathbf{x}(1-P(y=+\mid\mathbf{x}))$ (gradient with step size = 1)

  If P(+ | ***x***) is close to 1, make very little update

  Otherwise make ***w*** look more like ***x***, which will increase P(+ | ***x***)

- Update for ***w*** on negative example $= \mathbf{x}(-P(y=+\mid\mathbf{x}))$

  If P(+ | ***x***) is close to 0, make very little update

  Otherwise make *w* look less like ***x***, which will decrease P(+ | ***x***)

- Let *y* = 1 for positive instances, *y* = 0 for negative instances.
- Can combine these updates as $\mathbf{x}(y-P(y=1\mid\mathbf{x}))$

Example

(1) *this movie was great! would watch again* +

(2) *I expected a great movie and left happy* +

(3) *great potential but ended up being a flop* —

f(***x₁***) = [1 1]

f(***x₂***) = [1 1]

f(***x₃***) = [1 0]

[contains *great*] [contains *movie*]

position 0 position 1

w = [0, 0] ⟶ *P*(*y = 1* | ***x₁***) = exp(0)/(1 + exp(0)) = 0.5 ⟶ *g* = [0.5, 0.5]

w = [0.5, 0.5] ⟶ *P*(*y = 1* | ***x₂***) = logistic(1) ≈ 0.75 ⟶ *g* = [0.25, 0.25]

w = [0.75, 0.75] ⟶ *P*(*y = 1* | ***x₃***) = logistic(0.75) ≈ 0.67 ⟶ *g* = [-0.67, 0]

w = [0.08, 0.75] …

$P(y=+|x) = \text{logistic}(w^\top x)$

pos upd: $\mathbf{x}(1-P(y=+\mid\mathbf{x}))$

neg upd: $\mathbf{x}(-P(y=+\mid\mathbf{x}))$

Regularization

- Regularizing an objective can mean many things, including an L2-norm penalty to the weights:

$$\sum_{j=1}^{m} \mathcal{L}(x_j, y_j) - \lambda \|w\|_2^2$$

- Keeping weights small can prevent overfitting
- For most of the NLP models we build, explicit regularization isn't necessary
  - We always stop early before full convergence
  - Large numbers of sparse features are hard to overfit in a really bad way
  - For neural networks: dropout and gradient clipping

Logistic Regression: Summary

- Model

$$P(y = +|x) = \frac{\exp(\sum_{i=1}^{n} w_i x_i)}{1 + \exp(\sum_{i=1}^{n} w_i x_i)}$$

- Inference

$$\mathrm{argmax}_y P(y|x)$$

$$P(y = 1|x) \geq 0.5 \Leftrightarrow w^\top x \geq 0$$

- Learning: gradient ascent on the (regularized) discriminative log-likelihood. Same interpretation as gradient descent on log-loss (in a few slides)

Perceptron/SVM

Perceptron

- Simple error-driven learning approach similar to logistic regression
- Decision rule: $\mathbf{w}^\top \mathbf{f}(\mathbf{x}) > 0$
  - If incorrect: if positive, $\mathbf{w} \leftarrow \mathbf{w} + \mathbf{f}(\mathbf{x})$

    if negative, $\mathbf{w} \leftarrow \mathbf{w} - \mathbf{f}(\mathbf{x})$

Logistic Regression

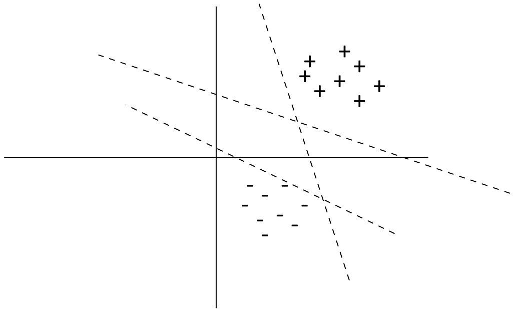
$$\mathbf{w} \leftarrow \mathbf{w} + \mathbf{f}(\mathbf{x})(1 - P(y = + \mid \mathbf{x}))$$

$$\mathbf{w} \leftarrow \mathbf{w} - \mathbf{f}(\mathbf{x})P(y = + \mid \mathbf{x})$$

- Guaranteed to eventually separate the data if the data are separable

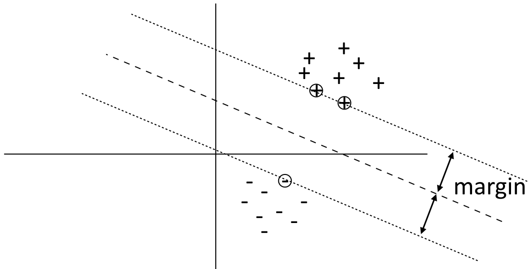
Support Vector Machines

- Many separating hyperplanes — is there a best one?



Support Vector Machines

- Many separating hyperplanes — is there a best one?



- Max-margin hyperplane found by SVMs

Perceptron and Logistic Losses

- Throughout this course: view classification as *minimizing loss*
- Let's focus on loss of a positive example
  - Perceptron: loss = $\begin{cases} 0 & \text{if } \mathbf{w}^\top \mathbf{f}(\mathbf{x}) > 0 \\ -\mathbf{w}^\top \mathbf{f}(\mathbf{x}) & \text{if } \mathbf{w}^\top \mathbf{f}(\mathbf{x}) < 0 \end{cases}$

    Take the gradient: no update if $\mathbf{w}^\top \mathbf{f}(\mathbf{x}) > 0$, else update with $+\mathbf{f}(\mathbf{x})$)
  - Logistic regression: loss = — log P(+|$\mathbf{x}$)

    (maximizing log likelihood = minimizing negative log likelihood)

Gradient Updates on Positive Examples

Logistic regression

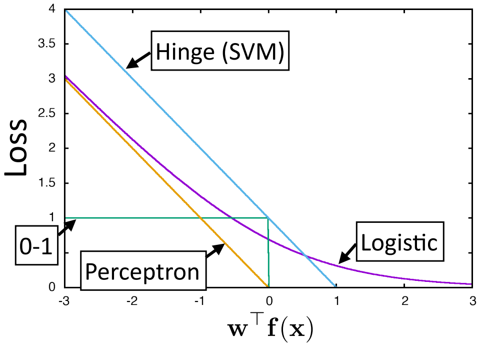
$$\mathbf{f}(\mathbf{x})(1 - \text{logistic}(\mathbf{w}^\top \mathbf{f}(\mathbf{x})))$$

Perceptron

$$\mathbf{f}(\mathbf{x}) \text{ if } \mathbf{w}^\top \mathbf{f}(\mathbf{x}) < 0, \text{ else } 0$$

SVM (ignoring regularizer)

$$\mathbf{f}(\mathbf{x}) \text{ if } \mathbf{w}^\top \mathbf{f}(\mathbf{x}) < 1, \text{ else } 0$$

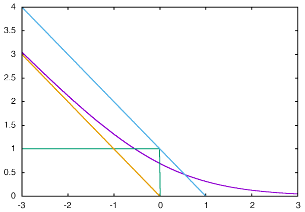


*sign of gradients flipped to give intuitive update

Optimization

Statistical Modeling

- Four elements of a structured machine learning method:
  - Model: probabilistic, max-margin, deep neural network
  - Objective



  - Inference: just maxes and simple expectations so far, but there can be other questions too (e.g. posterior over a variable)
  - Optimization: **gradient descent**

Optimization

- Stochastic gradient descent

$$\mathbf{w} \leftarrow \mathbf{w} - \alpha \mathbf{g} \qquad \mathbf{g} = \frac{\partial}{\partial \mathbf{w}} \mathcal{L}$$

  - Very simple to code up
  - “First-order” technique: only relies on having gradient
  - Can avg gradient over a few examples and apply update once (minibatch)
  - Setting step size is hard (decrease when held-out performance worsens?)
- Newton’s method
  - Second-order technique
  - Optimizes quadratic instantly

$$\mathbf{w} \leftarrow \mathbf{w} - \left(\frac{\partial^2}{\partial \mathbf{w}^2} \mathcal{L} \right)^{-1} \mathbf{g}$$

Inverse Hessian: *n* x *n* mat, expensive!

- Quasi-Newton methods: L-BFGS, etc. approximate inverse Hessian

AdaGrad

- Optimized for problems with sparse features
- Per-parameter learning rate: smaller updates are made to parameters that get updated frequently

$$w_i \leftarrow w_i + \alpha \frac{1}{\sqrt{\epsilon + \sum_{\tau=1}^{t} g_{\tau,i}^2}} g_{t_i}$$

(smoothed) sum of squared gradients from all updates

- Generally more robust than SGD, requires less tuning of learning rate
- Other techniques for optimizing deep models — more later!

Duchi et al. (2011)

Implementation

- Supposing *k* active features on an instance, gradient is only nonzero on *k* dimensions

$$\mathbf{w} \leftarrow \mathbf{w} - \alpha \mathbf{g} \qquad \mathbf{g} = \frac{\partial}{\partial \mathbf{w}} \mathcal{L}$$

- *k* < 100, total num features = 1M+ on many problems
- Be smart about applying updates!
- In PyTorch: applying sparse gradients only works for certain optimizers and sparse updates are very slow.

Sentiment Analysis

Sentiment Analysis

this movie was great! would watch again +

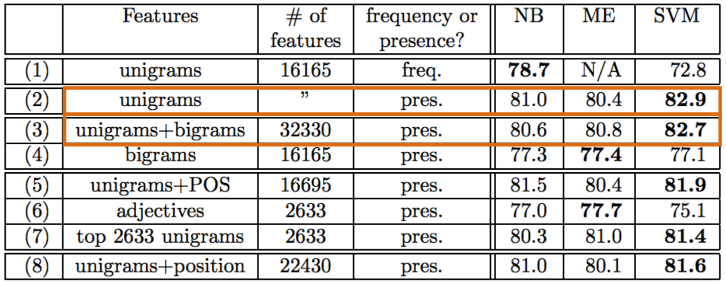
the movie was gross and overwrought, but I liked it +

this movie was not really very enjoyable —

- Bag-of-words doesn't seem sufficient (discourse structure, negation)
- There are some ways around this: extract bigram feature for "*not* X" for all X following the *not*

Bo Pang, Lillian Lee, Shivakumar Vaithyanathan (2002)

Sentiment Analysis

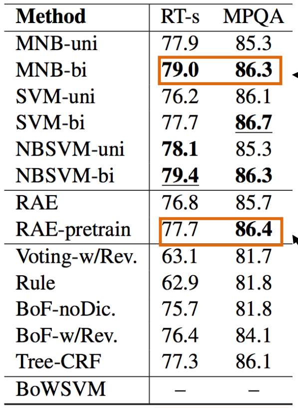


	Features	# of features	frequency or presence?	NB	ME	SVM
(1)	unigrams	16165	freq.	**78.7**	N/A	72.8
(2)	unigrams	”	pres.	81.0	80.4	**82.9**
(3)	unigrams+bigrams	32330	pres.	80.6	80.8	**82.7**
(4)	bigrams	16165	pres.	77.3	**77.4**	77.1
(5)	unigrams+POS	16695	pres.	81.5	80.4	**81.9**
(6)	adjectives	2633	pres.	77.0	**77.7**	75.1
(7)	top 2633 unigrams	2633	pres.	80.3	81.0	**81.4**
(8)	unigrams+position	22430	pres.	81.0	80.1	**81.6**

- Simple feature sets can do pretty well!

Bo Pang, Lillian Lee, Shivakumar Vaithyanathan (2002)

Sentiment Analysis



Method	RT-s	MPQA
MNB-uni	77.9	85.3
MNB-bi	**79.0**	**86.3**
SVM-uni	76.2	86.1
SVM-bi	77.7	**86.7**
NBSVM-uni	**78.1**	85.3
NBSVM-bi	**79.4**	**86.3**
RAE	76.8	85.7
RAE-pretrain	77.7	**86.4**
Voting-w/Rev.	63.1	81.7
Rule	62.9	81.8
BoF-noDic.	75.7	81.8
BoF-w/Rev.	76.4	84.1
Tree-CRF	77.3	86.1
BoWSVM	–	–
Kim (2014) CNNs	81.5	89.5

Naive Bayes is doing well!

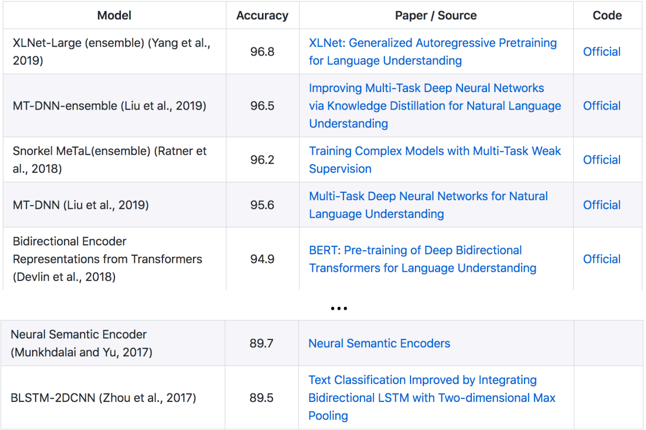
Ng and Jordan (2002) — NB can be better for small data

Before neural nets had taken off — results weren't that great

Wang and Manning (2012)

Sentiment Analysis

- Stanford Sentiment Treebank (SST) binary classification
- Best systems now: large pretrained networks
- 90 -> 97 with good NN models



Model	Accuracy	Paper / Source	Code
XLNet-Large (ensemble) (Yang et al., 2019)	96.8	XLNet: Generalized Autoregressive Pretraining for Language Understanding	Official
MT-DNN-ensemble (Liu et al., 2019)	96.5	Improving Multi-Task Deep Neural Networks via Knowledge Distillation for Natural Language Understanding	Official
Snorkel MeTaL(ensemble) (Ratner et al., 2018)	96.2	Training Complex Models with Multi-Task Weak Supervision	Official
MT-DNN (Liu et al., 2019)	95.6	Multi-Task Deep Neural Networks for Natural Language Understanding	Official
Bidirectional Encoder Representations from Transformers (Devlin et al., 2018)	94.9	BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding	Official
…			
Neural Semantic Encoder (Munkhdalai and Yu, 2017)	89.7	Neural Semantic Encoders	
BLSTM-2DCNN (Zhou et al., 2017)	89.5	Text Classification Improved by Integrating Bidirectional LSTM with Two-dimensional Max Pooling	

`https://github.com/sebastianruder/NLP-progress/blob/master/english/sentiment_analysis.md`

Takeaways

- Logistic regression, SVM, and perceptron are closely related; we'll use logistic regression mostly, but the exact loss function doesn't matter much in practice
- All gradient updates: "make it look more like the right thing and less like the wrong thing"
- Next time: multiclass classification