Learning from Data
Lecture 6: Linear Regression
Semi-Supervised Learning

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Topics

1. Linear Regression
2. Semi-supervised learning
   - Bootstrapping
   - Co-training
   - Active learning
   - Distant Supervision
3. Feature analysis
4. Shared Task

Classification vs Regression

create models of prediction from gathered data

- classification
  the dependent variables are categorical
  - input x: feature vector
  - output: **discrete class label**

- regression
  the dependent variables are numerical
  - input x: feature vector
  - output y: **continuous value**

Example: Predicting housing prices in the Netherlands

Data

training data

size m^2	price
57	150,000
90	210,000
30	90,000

Data

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x (input) y (output)

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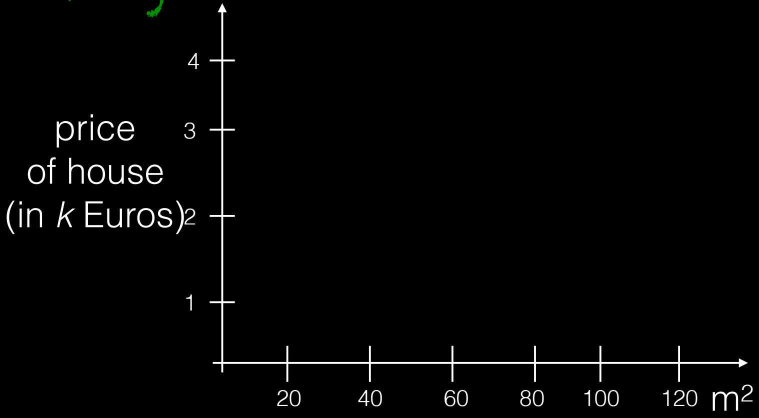
x (input) y (output)

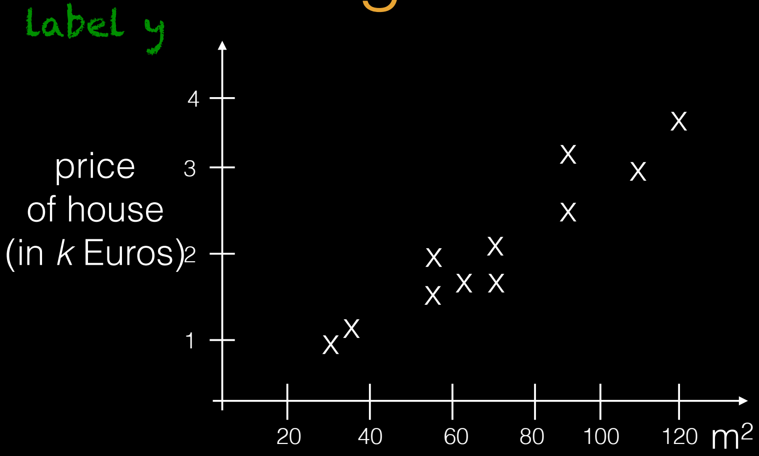
$$\langle x, y \rangle$$

Regression

label y



Regression



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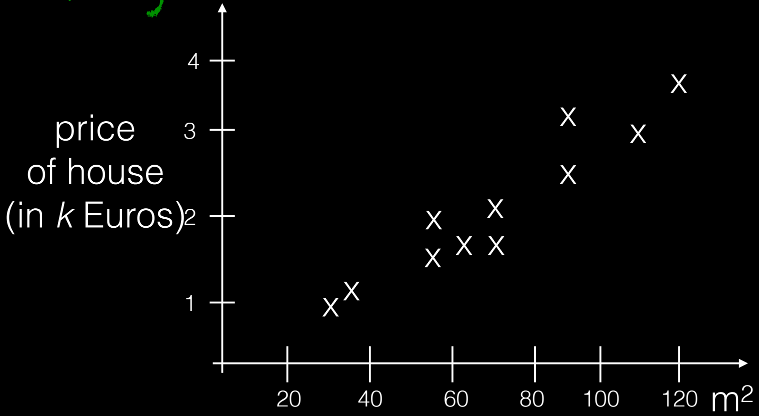
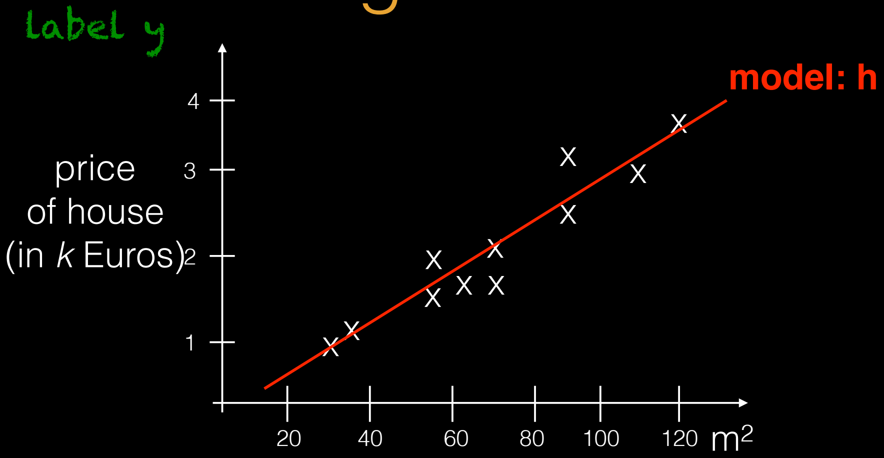


regression: predict numeric (continuous) output

Regression



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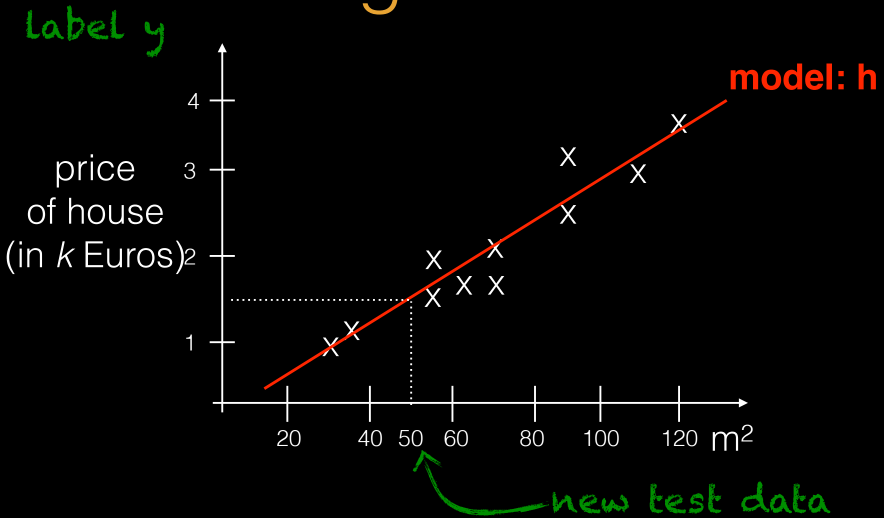

regression: predict numeric (continuous) output

Generalisation

experience
(training data)

size m^2	price
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Generalisation

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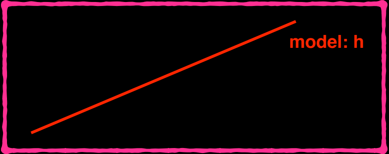
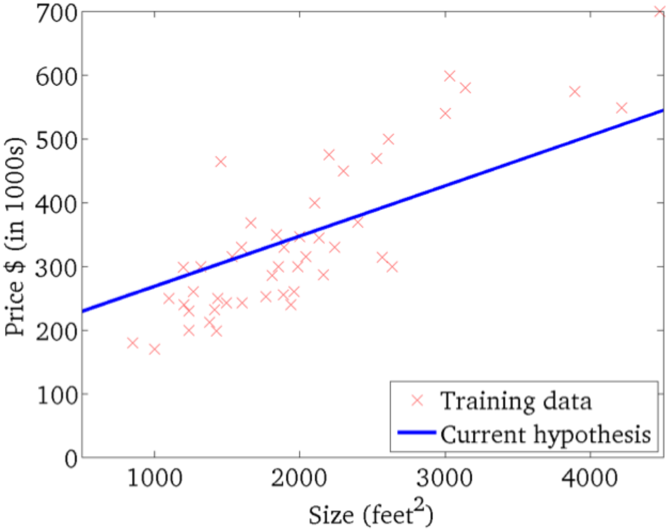


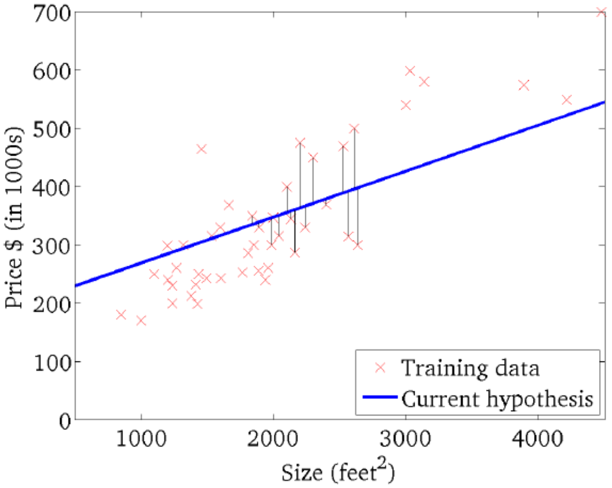
Modelling in LR

- Fitting a model to training data that generalises well to unseen data
- Hypothesis/model/function
- The model is a function that knows how to map x to y

One-feature example



Error as vertical lines



Mean Squared Error (MSE)

How close is a regression line to a set of points?

General idea:

- take the distances from the actual points to the regression line (distance = error)
- square them (necessary to remove any negative signs; also gives more weight to larger differences)
- take average

Mean Squared Error (MSE)

Steps to calculate the MSE from a set of X and Y values:

- find the regression line
- insert your X values into the linear regression equation to find the new Y values (Y)
- subtract the new Y value from the original to get the error
- square the errors
- add up the errors
- find the mean

interpretation: the smaller the MSE, the closer to the best fit

Regression in `scikit`

- training (fitting)
- testing
- evaluating

```
>>> from sklearn import linear_model
>>> from sklearn.metrics import mean_squared_error

>>> lr = linear_model.LinearRegression()
>>> lr.fit(Xtrain, Ytrain)

>>> Yguess = lr.predict(Xtest)
>>> mean_squared_error(Ytest, Yguess)

# worked out:
>>> np.mean((Yguess - Ytest) ** 2))
```

Hypothesis

- Parameters (weights) represented by Theta, Θ
- With one feature only:

$$h_\Theta(x) = \Theta_0 + \Theta_1 x_1$$

- Multiple features:

$$h_\Theta(x) = \Theta_0 + \Theta_1 x_1 + \Theta_2 x_2 + ... + \Theta_n x_n$$

for convenience, $x_0 = 1$

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example interpretation:
price $= \Theta_0 + \Theta_1$Size $+ \Theta_2$Age $+ \Theta_3$#Floors...

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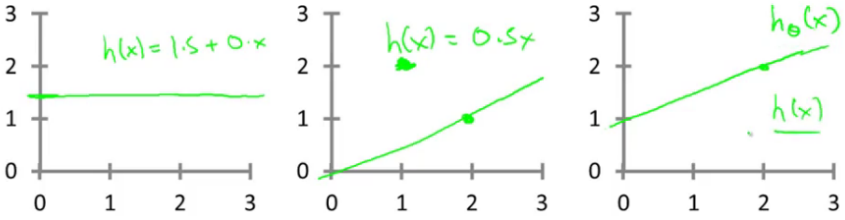

$\rightarrow \theta_0 = 1.5$	$\rightarrow \theta_0 = 0$	$\rightarrow \theta_0 = 1$
$\rightarrow \theta_1 = 0$	$\rightarrow \theta_1 = 0.5$	$\rightarrow \theta_1 = 0.5$

https://www.coursera.org/learn/machine-learning/lecture/rkTp3/cost-function

Cost function J

How to fit the best possible model to our training data?

- find Θs that minimise the cost
- and because cost is squared error, then
- minimising squared difference between predicted output and true output $(h_{\Theta}(x) - y)^2$

semi-supervised learning

What if there is no y?

x $\longrightarrow$?

What if there is no y?

$\mathbf{x} \longrightarrow \mathbf{?}$

unlabeled
data

What if there is no y?

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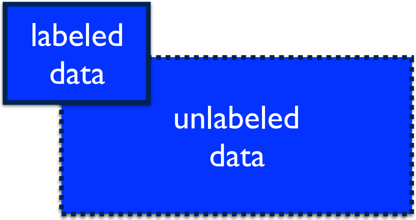

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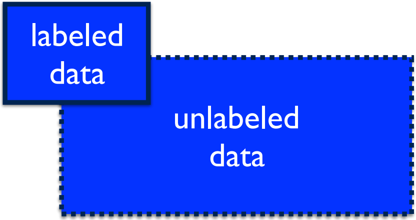

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$$\mathbf{x} \longrightarrow \mathbf{?}$$

unsupervised learning

unlabeled data

semi-supervised learning

labeled data

unlabeled data

What is SSL? More formally

- Learning from both labeled and unlabeled data:
  - l labeled instances $\{(\mathbf{x}_i, y_i)\}_{i=1}^{l}$ and
  - u unlabeled instances $\{\mathbf{x}_j\}_{j=l+1}^{l+u}$, usually $u >> l$
- **Goal**: better classifier than from labeled data alone

Anti-SSL arguments

- "We'll find the time and money to annotate more labeled data"
- Hmm, but:
  - Annotating PT WSJ took a decade!
  - What about building a NER for, say, Irish? Who is going to annotate it for me?

Semi-supervised learning

use a little amount of labelled data + a large amount of unlabelled data

Semi-supervised learning

use a little amount of labelled data $+$ a large amount of unlabelled data

it's a matter of getting help

- the classifier gets help from itself $\rightarrow$ bootstrapping
- the classifier gets help from another classifier $\rightarrow$ co-training
- the classifier gets help from a human $\rightarrow$ active learning

bootstrapping

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aka **self-training**: the classifier uses its own predictions to teach itself

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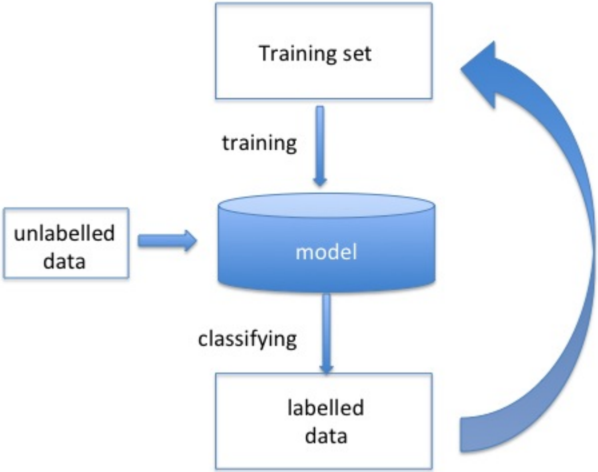
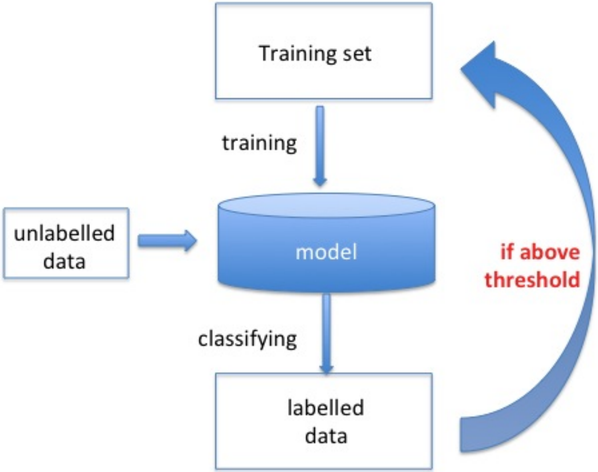
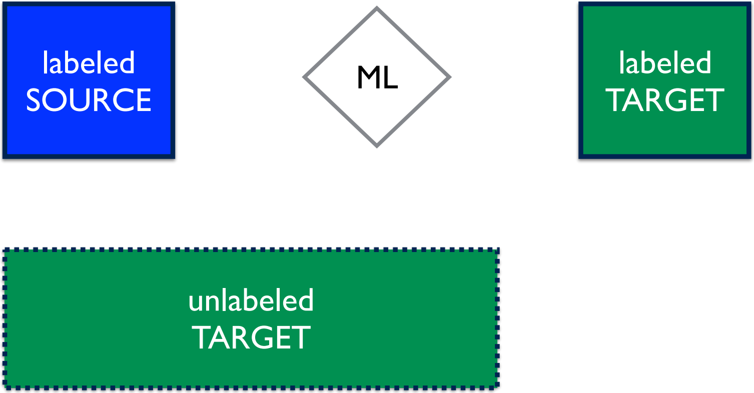
Bootstrapping



Bootstrapping



Self-training



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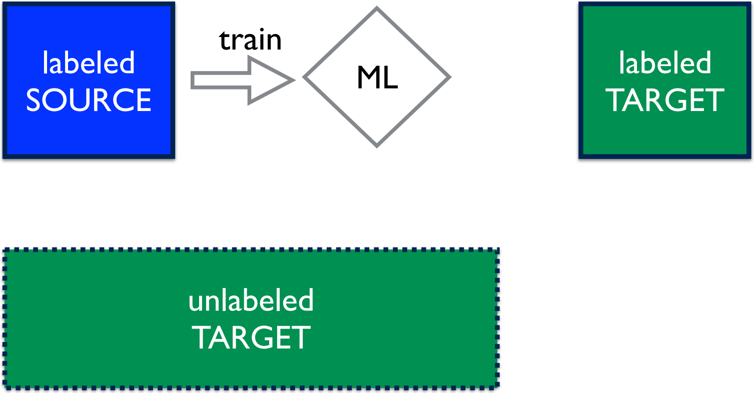

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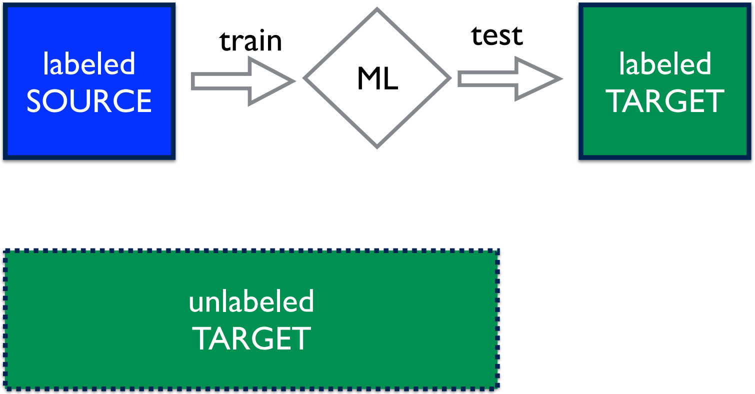

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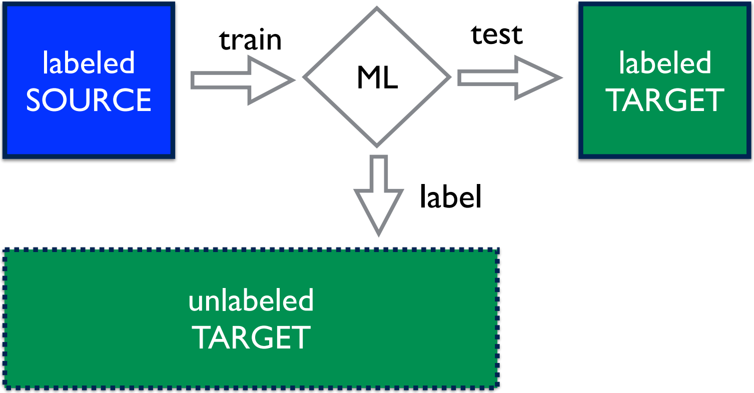

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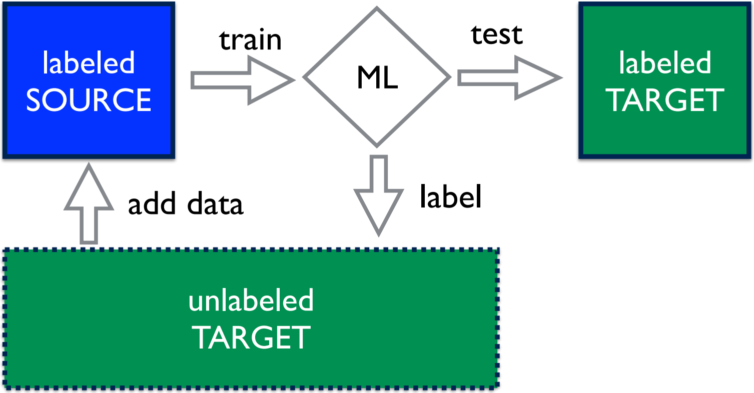

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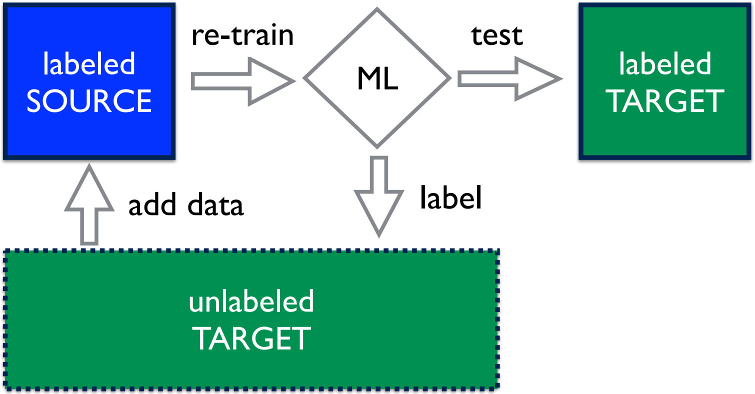

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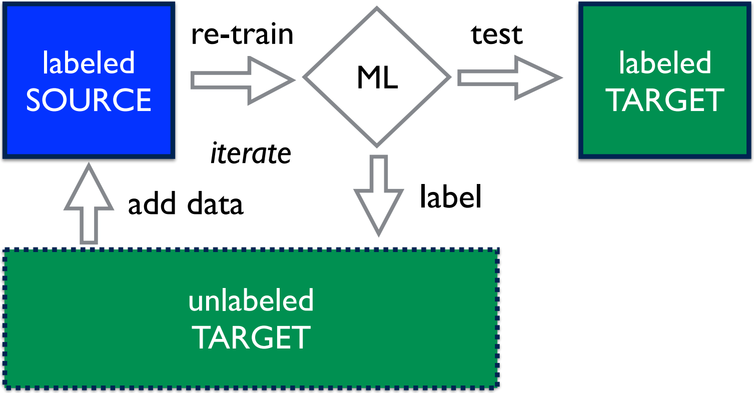


Bootstrapping or Self-training

parameters:

- iterations: number of iterations
- pool size: number of examples selected from the unlabeled set U for annotation at each iteration.
- growth size: number of most confidently labeled examples that are added at each iteration to the set of labeled data L.

Bootstrapping or Self-training

- useful when very little but very good data is available and it's too costly to annotate more
- if the data is very skewed it can be problematic to safely assign the low frequency class(es)
- the choice of initial seed examples is crucial

→ this is different from "bootstrap" as used in statistics!

co-training

Co-training

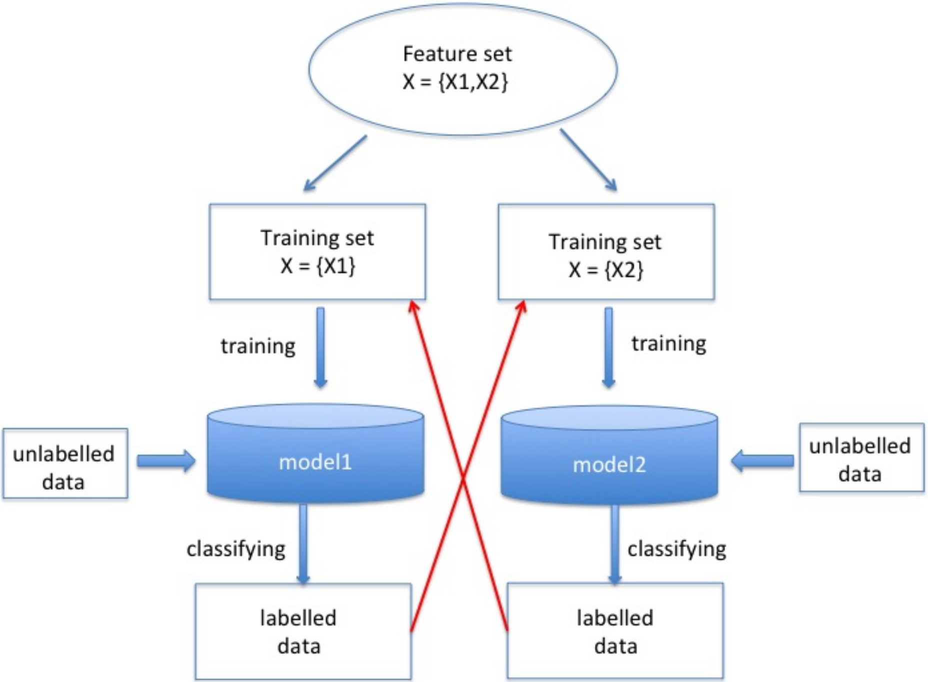
- two sufficient and independent sets of features: an instance X is $X = (X_1, X_2)$

  $P(X_1|X_2, Y) = P(X_1|Y)$

  $P(X_2|X_1, Y) = P(X_2|Y)$

- independent sets are different *views*
- independent views can be informative
- exploit two views of the same phenomenon to acquire more labelled data for training

(ref: Blum & Mitchell 1998)


Feature set
X = {X1,X2}
Training set
X = {X1}
Training set
X = {X2}
training
training
unlabelled
data
model1
model2
unlabelled
data
classifying
classifying
labelled
data
labelled
data

active learning

Active learning

excellent slides by Piyush Rai

distant supervision

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use *reasonably safe proxies* to obtain training labels

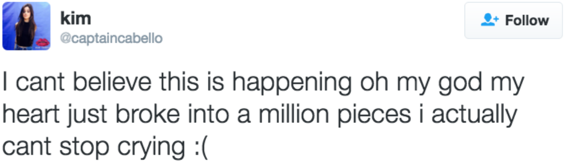
Distant Supervision: examples

Distant Supervision: examples


Weston Dennis
@G2Westballz
Follow

I'll be back even stronger. See me at g4. GG's to hbox and every one else I played. Fun tourney great crowd. I missed this :)

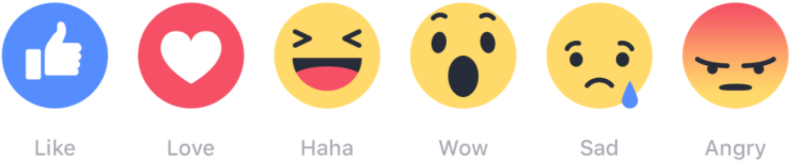
⇒ positive


kim
@captaincabello
Follow

I cant believe this is happening oh my god my heart just broke into a million pieces i actually cant stop crying :(

⇒ negative

Distant Supervision: examples



how to understand the contribution of features

Choosing features

pos tagging identity of the word being processed, identity of the words immediately to the left and right, part-of-speech tag of the word to the left, function/content word

sentiment analysis positive/negative trait in a lexicon, id of the speaker, discourse relations (contrast, concession, ...)

authorship verification character n-grams, pos n-grams, sentence length, punctuation, ...

named entity recognition ...

Feature analysis

- leave one out (feature ablation): remove one single feature at the time and re-train and re-test the classifier to compare results with and without that feature.

  $\rightarrow$ The most useful features are those that cause the biggest drop in performance

- single feature classifier: train and test the classifier with just one feature at the time.

  $\rightarrow$ The most useful features are those that yield the highest performance

Leave one out

- also known as *ablation*
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- often used with *groups* of features

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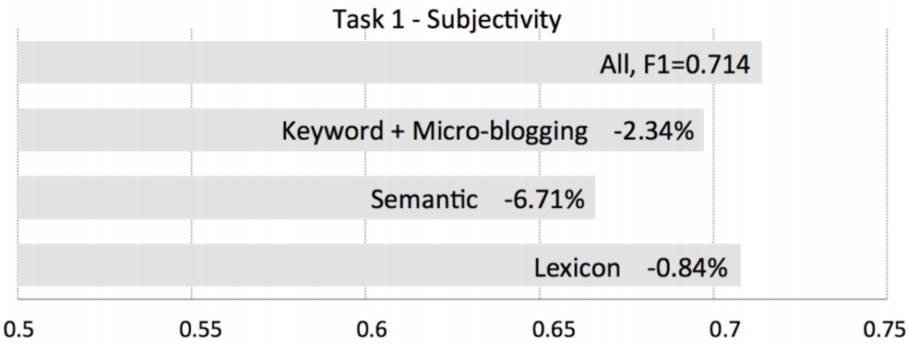

Single feature classifier

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shared task

Shared Task

also known as *challenge*

- evaluating systems on the same data for a proper comparison
- assessing (and sharing) state of the art systems and methods
- converging efforts on common interests
- creating data

Shared Task

Procedure:

- research groups or programme committees propose a series of tasks
- the shared task's organisers make a sample available
- teams register
- teams receive training data
- teams develop their systems
- teams receive test data
- after about one week teams return their outputs/systems to the organisers
- organisers evaluate systems according to predefined metrics
- teams and organisers write reports
- workshop(s)

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also known as *challenge*

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Semeval 2016
Semeval 2017