DAY 5: EVALUATION

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POS-TAGGING REMINDER

PTB tags

Return	now	to	your	quarters	and	I	will	send	you	word	of	the	outcome
V	Adv	Prep	Pro	N	CC	Pro	V	V	Pro	N	Prep	Det	N
VB	RB	IN	PP$	NNS	CC	PP	MD	VB	PP	NN	IN	DT	NN

- Word may take many POS tags
- Model tries to **disambiguate**
- Use statistics from *corpus*
- Many models: features, statistics, ...

POS	Example
Noun	*The dog ate the bone*
Verb	*The dog ate the bone*
Adjective	*The big dog ate the bone*
Adverb	*He ate the bone quickly*
Pronoun	*He ate my bone*
Determiner	*The dog ate that bone*
Preposition	*He chewed with his teeth*
Coordinating conjunction	*He chewed and growled*

POS TAGGER OUTPUT

- You've got a new POS tagging method
- Trained model
- Try on some example inputs...
- Output looks good! – better than existing method

Questions:

- **Real** improvement, or did we get lucky?
- **How big** is improvment?
- **How general** is improvment?
  Will it help in practice on lots of real data?

EVALUATION

- Scientific method: make **hypotheses**, test them
- Evaluation = testing
- Why?
  - **Public review**: convince others your method is good
  - **Internal review**: unbiased validation of improvement
  - And **quantification**
  - Systems might **evaluate themselves** to improve

EVALUATION IN NLP

- Much of today probably familiar from e.g. ML courses
- We'll cover much from scratch
- Some aspect specific to NLP
- Some NLP issues require special attention

EVALUATION

(Close as possible)

- Unbiased system comparison
- Compare: *models*, *training sets*, *methods*, *frameworks*
- Use existing evaluation if possible:
  test data, methods, metrics
- Design evaluation before developing model: success criteria
- Desiderata:
  - **Unbiased**
  - **Reliable**: enough data
  - **Representative** of target domain (often: as general as possible)
  - **Reproducible**: others can repeat, compare other models

TYPES OF EVALUATION

Evaluating *method* for a *task*

Intrinsic: test inherent to task

- POS tagging: tag accuracy
- Parsing: dependency F-score (see later)
- Search: recall of relevant documents

Extrinsic: test of effect on other, *downstream* tasks

- POS tagging: affect on parsing performance
- Parsing: improvement in relations extract from text (IE)
- Search: perceived improvement of tool for users

REUSING TEST DATA

- Many tasks: standard test sets exist
- Advantages of reusing test data:
  - **Direct comparison** to earlier work
  - Laborious **annotation** work reused
  - Avoid **unintentional bias**

More later

E.g. towards your method

- Drawbacks: later

STANDARD EVALUATION DATASETS

- Examples for specific tasks:
  - *Penn Treebank*: syntactic parsing
  - *Brown Corpus*: POS tagging (and others)
- Preparation and annotation: huge effort
  - E.g. PTB: millions of words with syntactic trees
  - Annotated over 3 years
- Often carefully chosen data: representative, balanced, etc

SHARED TASKS

- **Competition** on particular task
- Provided: ← Often available afterwards / Reuse for later evaluation
  - Training data
  - Detailed task description
  - Test data (released later)
- Compare, publish best-performing methods

- E.g. SemEval-2018
  - *Irony detection in Tweets*
  - *Argument reasoning comprehension* (resources)
  - *Semantic relation extraction in scientific papers*

HOW DO WE KNOW WHAT'S GOOD?

Input sentence — POS tagger 1 — POS tagger 2 — Gold standard annotations

	He	*gazed*	*again*	*at*	*the*	*scene*	*below*	*,*	*and*	*now*
1:	PRP	VBD	RB	IN	DT	NN	JJ	,	CC	RB
2:	PRP	VBD	RB	IN	DT	NN	IN	,	CC	RB
GS:	PRP	VBD	RB	IN	DT	NN	JJ	,	CC	RB

noted	*one*	*difference*	*from*	*the*	*accustomed*	*Porovian*	*landscape*	*.*
VBN	CD	NN	IN	DT	JJ	NNP	NN	.
VBN	CD	NN	IN	DT	VBN	JJ	NN	.
VBN	CD	NN	IN	DT	JJ	JJ	NN	.

	Num correct	Total tags	**Accuracy**
System 1	16	18	$16/18 = 89\%$
System 2	15	18	$15/18 = 83\%$

METRIC: ACCURACY

- Simple metric: **accuracy**

$$\frac{\#\text{ correct}}{\text{total words}}$$

- Measure over *large* test corpus
- Not always suitable
- Other suitable in many circumstances
- Some more specific to language tasks: coming up

LANGUAGE MODELLING ACCURACY?

- Remember: LM is prob dist over sentences

$$p(W)$$

- Typically modelled as dist over words given earlier words

$$p(w_i|w_0,\ldots,w_{i-1})$$

- Two LMs produce different predictions

$$p(w_i|w_0,\ldots,w_{i-1},LM_0)p(w_i|w_0,\ldots,w_{i-1},LM_1)$$

- Could compare using accuracy

$$argmax_w(p(w|w_0,\ldots,w_{i-1})) \stackrel{?}{=} w_i$$

- Large vocabulary: top prediction rarely correct

EVALUATING A LANGUAGE MODEL

- Observed word should receive high probability
- but others are not *wrong*
- Models produce **distributions** over words
- Compare **probabilities** of **observed words**
- Idea: measure mean probability of observed words
- Typical measure: **perplexity**

PERPLEXITY

- Information theoretic measure
- How **surprised** model is on average by each word

$$2^{-\frac{1}{m}log_2(p(w_0,\ldots,w_{m-1}))}$$

- For LM whose context is previous words:

$$2^{-\frac{1}{m}\sum_{i=0}^{m} log_2(p(w_i|w_0,\ldots,w_i))}$$

- Lower is better

EXAMPLE LM PERPLEXITIES

Evaluation on Penn Treebank texts (890k toks)

Model	**Perplexity**
AWD-LSTM, *mixture of softmaxes* (2018)	54.44
LSTM (2014)	82.7
Smoothed 5-gram (1996)	141.2

Evaluation on WikiText-2 (Wikipedia text, 2M toks)

Model	**Perplexity**
AWD-LSTM, *mixture of softmaxes* (2018)	61.45
Variational LSTM (2016)	87.0

PERPLEXITY

- What does *54.44 PPL* mean?
- Is it good?
- Depends on:
  - test corpus: how hard is it to predict?
  - training corpus: how big / representative?
- Compare models on same training + test corpus

METRICS

- *Accuracy* and *perplexity* are **evaluation metrics**
- Compare output to *gold standard*
- Numeric measure of correctness
- Different metrics appropriate for different tasks
- Sometimes multiple: capture
  - different aspects of task
  - different types of 'correctness'

SOME OTHER METRICS

- Other commonly used metrics:
  - **P**recision
  - **R**ecall
  - **F**-score
- Common generally in ML
- Very common in NLP evaluation

PRECISION & RECALL

- **Task**: detect relevant items in large corpus
- E.g. information retrieval / search ← More on day 7
- **Gold standard**: annotated set of all relevant items
- System tags all items as *relevant* / *irrelevant*

$$\text{Precision (P)} = \frac{\text{True positives}}{\text{True positives} + \text{False positives}}$$

$$\text{Recal (R)} = \frac{\text{True positives}}{\text{True positives} + \text{False negatives}}$$

PRECISION & RECALL

- **Task**: detect relevant items in large corpus
- E.g. information retrieval / search ← More on day 7
- **Gold standard**: annotated set of all relevant items
- System tags all items as *relevant* / *irrelevant*

True positives

$$\text{Precision (P)} = \frac{\#\text{ relevant GS items tagged as relevant}}{\#\text{ items tagged as relevant}}$$

$$\text{Recall (R)} = \frac{\#\text{ relevant GS items tagged as relevant}}{\#\text{ GS relevant items}}$$

PRECISION & RECALL

$$\text{Precision (P)} = \frac{\#\text{ relevant GS items tagged as relevant}}{\#\text{ items tagged as relevant}}$$

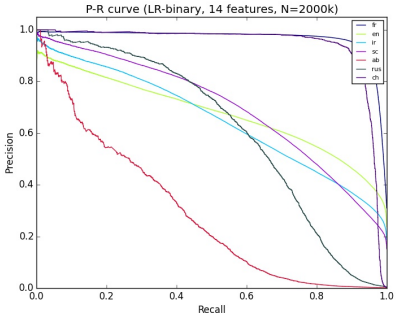
How much can we rely on returned results being correct?

$$\text{Recall (R)} = \frac{\#\text{ relevant GS items tagged as relevant}}{\#\text{ GS relevant items}}$$

How much can we rely on system to find all correct results?

- Sometimes one more important than other
- Often systems can trade off between them

PRECISION-RECALL CURVE



Graph from KubiK888 on SO

F-SCORE

- Combine into one metric: **F-score** / **F-measure**
- Harmonic mean of P and R

$$F_\beta = \frac{(\beta^2 + 1)PR}{\beta^2 P + R}$$

- Most often, just use $\beta = 1$:

$$F_1 = \frac{2PR}{P + R}$$

BASELINES

- You've got a brand new, swanky POS tagger
- Output looks good, but how reliable is this?
- Evaluate on unseen test set
- Measure accuracy
- Compare to existing tagger: better!
- Looks good, but how hard is this task/dataset?

System	Accuracy (%)
MyTagger	94.5
OldTagger	92.3

BASELINES

- How hard is this task/dataset?
- Also compare to **baselines**
- Simple models using much less data, inference, training time...
- Tells us
  - how much these things are buying us
  - how hard task is
  - whether we're wasting our time

A SIMPLE BASELINE

Some baselines for POS tagger:

- Random choice
  - 20 tags → expect 5%
- Majority class
  - Most frequent tag: `Noun`
  - 61.5% of words in test set
  - Acc 61.5% if always `Noun`
- Ignore context
  - For each word, use its most frequent tag in training set
  - '*Unigram*' model (like unigram-HMM)

System	Acc (%)
MyTagger	94.5
OldTagger	92.3
Random	5
Majority class	61.5
Unigram	90.2

A SIMPLE BASELINE

- In this case, unigram does well
- Neither tagger does *much* better
- That 2-5% could be very hard
- Need some error analysis
- Maybe need
  - evaluation/analysis that explains differences
  - harder test set, focussed on difficult cases

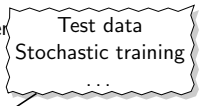
System	Acc (%)
MyTagger	94.5
OldTagger	92.3
Random	5
Majority class	61.5
Unigram	90.2

CEILINGS

- Baslines establish *lower bounds*
- **Ceiling**: *upper bound*
- Best we can ever expect from model
- Probably unachievable goal
- Human performance: agreement between annotators
- Or perfect knowledge of some part of task
  - Quantify how hard parts of the task are
  - How well model does on different parts

SIGNIFICANCE

- Measuring things, comparing measurements
- What and how depends on task
- Important question in all cases:
  Are the differences **significant**
- Are the differences down to chance? Or something more?



Is a model *significantly* better than *baseline*?
Is it *significantly* worse than *ceiling*?

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EXAMPLE: TOSSING A COIN

- Toss a coin **40** times
- Get **heads 17** times, **tails 23**
- Expected value of fair coin: **20**
- Is different *significant*?
  - Yes → (probably) not a fair coin
  - No → (probably) a fair coin

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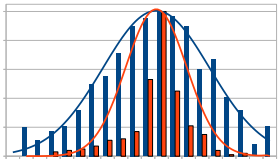
NORMAL DISTRIBUTIONS

- Significance measurement is a complex area
- Simple basic idea is simple:

  Measure difference in terms of standard deviations

- **Standard deviation**: how *representative* is mean?
- More outliers / further from mean → mean less representative
  → higher standard deviation



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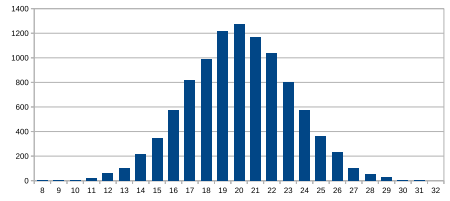
DISTRIBUTION OF A FAIR COIN

- Many coin toss trials: e.g. toss 40×, repeat 100k×
- Distribution approaches **normal distribution**
- Mean $\simeq$ 50%, but range of outcomes plausible



- Even result >2 std devs out will come up ∼1/20 trials

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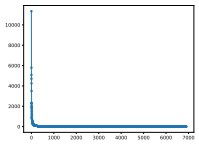
WHICH SIGNIFICANCE TEST?

- **Parametric** when underlying distribution is **normal**
  - **t-test**, **z-test**, . . .
  - Check test assumptions appropriate for specific case
- **Non-parametric** otherwise
  - **McNemar's test** or variants
  - Usually non-parametric in NLP: *Zipf's law*, not normal



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GOLD STANDARD DATA

- Data annotated with 'true' labels
- Human judgement of correct labels, ratings, . . .
- GS data often need for training
  - Supervised methods
- Also for evaluation, as we've seen

Important: evaluation is always on **unseen** data

TEST DATA

- **Unseen test data** is sacrosanct
- Unseen
  - by *model*: separate from training data
  - by *you*: avoid influencing model/method design, feature selection, . . .
  - by *evaluation routine*: don't run during development, only in final comparison
- All violations can produce **overfitting** in some form
  - How?

TRAINING AND TESTING

- **Overfitting** → model good on test set, not on other data
- Overestimates performance on unseen data, 'in the wild'
- Separate **training** and **test** sets
- Typical procedure:
  1. Collect GS data (annotation)
  2. Split into training+test (e.g. 80 : 20 or 90 : 10)
  3. Training set: examine data, train models, compare, . . .
  4. Test set: evaluate and report results

DEVELOPMENT

- Models have *hyperparameters*: want to set empirically
  E.g. *n* in n-gram LM, or smoothing parameters
- Need to test models before final evaluation
  - Compare model types, architectures, etc
  - Check modelling hypotheses
  - Test for overfitting
- Common solution: keep aside part of training set
- **Development** / **validation** set (devset): e.g. 80 : 10 : 10

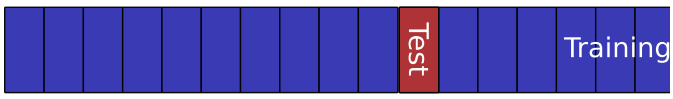
LIMITED DATA

- Small corpus: splitting can leave too little for testing
- Or for training
- Alternative: **cross validation**

- Still need held-out **test set** for final evaluation

CROSS VALIDATION

- Can also use cross validation for **evaluation**
- Useful when annotated data extremely scarce
- More test data: results more representative
- Results less sensitive to random split
- But caution!
- Whole corpus must be **blind**: don't look at it during development
- Harder to avoid *bias* in long run

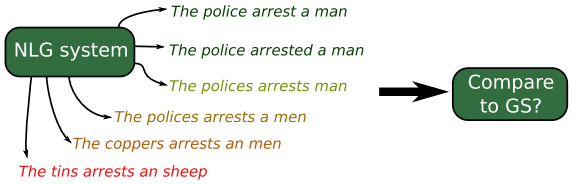


CHOOSING A DATASET

- Consider existing training/test sets
  - Someone else has done hard work for you
  - Usually carefully thought out: balanced, etc
- Things to consider:
  - **representative** of target domain
  - **annotated**/suitable to annotate
  - **large** enough
  - **balanced** (in various ways)
- If necessary, annotate: a lot of work

HUMAN EVALUATION

- Alternative: get people to asses system output
- Often replicating this with data-driven evaluation
  (Not always: sometimes data removes bias)
- Sometimes necessary or preferable



HUMAN EVALUATION

- Many difficult issues involved: no time today
- Some challenges:
  - Difficult to replicate/compare to later
  - Smaller test set: less representative
  - Costly
- **Inter-annotator agreement**
  - Important to measure: often low
  - Multiple judgements per example
  - Lower IAA: more judgements

CROWD SOURCING

- Popular for **human evaluation** and **annotation**
- Small money for small tasks
- E.g. *Amazon Mechanical Turk*
- *Much* less reliable than experts / known evaluators
- Cheap annotation of lots of data
- Many issues with quality
  - Need **redundancy**: lots of annotations per example
  - **Test questions** and other checks for bad/malicious annotators

ERROR ANALYSIS

- Broad metrics give overview, but don't tell us everything
- Beware *Zipf*: rare stuff often important
- **Error analysis**: more than just summary statistics
- More insight into what's going on
  - Find patterns in results:
    e.g. better scores on particular type of inputs
  - Qualitative insight: what type of mistakes does system make?
    → Different models capture different things?
  - Find bugs
  - Focus future work
- Evaluation sanity check: are 'better' models actually better?

CONFUSION MATRICES

Good way to find common problems

Example: POS tagging errors

Predicted labels

Correct labels	IN	JJ	NN	NNP	RB	VBD	VBN
IN	–	2			7		
JJ	2	–	33	21	17	2	27
NN		87	–				2
NNP	2	33	41	–	2		
RB	22	20	5		–		
VBD		3	5			–	44
VBN		28				26	–

Diagonal: correct predictions

Example from J&M2 p190

CONFUSION MATRICES

Good way to find common problems

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High values: common mistakes

Example from J&M2 p190

CONFUSION MATRICES

	IN	JJ	NN	NNP	RB	VBD	VBN
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VBD		3	5			–	44
VBN		28				26	*dog*

Finland

Proper nouns (NNP) tagged as **common nouns** (NN).

Hard to distinguish in some contexts.
Important for **IE** and **MT**.

CONFUSION MATRICES

	IN	JJ	NN	NNP	RB	VBD	VBN
IN	–	2			7		
JJ	2	–	33	21	17	2	27
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eaten *ate*

Past participles (VBN) confused with **past tense** (VBD).

Important for finding edges of noun phrases:

Estimated counts are better than no counts.
He estimated counts for all categories.

YOU PLAY ANNOTATOR

Verb, noun or adjective?

- *We had been* **walking** *quite briskly*
- **Walking** *was the remedy, they decided*
- *Sandburg was a* **walking** *thesaurus of American folk music*
- *We all lived within* **walking** *distance of the studio*
- *A woman came along carrying an umbrella as a* **walking** *stick*
- *The Walking Dead premiered in the US on Oct 31 2010*

ANNOTATION MANUAL: PTB

- Penn Treebank: 36 POS tags
- Tagging guidelines: 34 pages

  'The temporal expressions yesterday, today and tomorrow should be tagged as nouns (NN) rather than as adverbs (RB). Note that you can (marginally) pluralize them and that they allow a possessive form, both of which true adverbs do not.'
- Tree bracketing guidelines: >300 pages!

MEASURING QUALITY

- Multiple people independently annotate same data
- Measure **inter-annotator agreement** (IAA)
- **Raw agreement rate**: proportion of labels in agreement
- If low, examine disagreement
  - More training
  - Refine guidelines
  - Reject some data
- More sophisticated measures account for:
  - Knowledge of annotation scheme (some things harder / more important)
  - Probability of agreement by chance
- **Upper bound** (*human ceiling*) for system accuracy on task

ANNOTATION

- Sometimes need new annotated corpus
- Some things to decide on to estimate **cost** (time and money):
  - Source data: genre, size, licensing
  - Annotation scheme: complexity, guidelines
  - Annotators: expertise, training
  - Annotation software: graphical?
  - Quality control: multiple annotation? adjudication?
- Competent annotator: some tasks are straightforward for most inputs
- Others not:
  - Ambiguous text
  - Grey areas between categories

ANNOTATION: NOT AS EASY AS YOU THINK

- Any annotation scheme has some **difficult cases**
- Grey areas, multiple plausible decisions
- Human language is flexible: cuts corners, changes over time
- Seen some examples already (POS tags, syntax)
  Much more on day 10
- Want annotations to be **clean**, **consistent**, **reliable**
- **Annotation manual**: important for producing consistent data and making annotators' job easier

ANNOTATION QUALITY

Even with good guidelines, annotations won't be perfect

- Simple errors (wrong button)
- Not reading full context
- Forgetting detail from guidelines
- Cases not anticipated by guidelines

How to measure quality of 'gold' data?

OVERFITTING ON A GRAND SCALE

- Another of overfitting: **long-term**
- Standard test set T
  - Everyone evaluates on T
  - All observe proper practices, keep T blind
  - Better models (on T) 'win', built on in further work
  - After 20 years, SOTA models excellent at T's
    - annotations
    - annotation type
    - task
    - domain
    - language
  - But no good outside these contexts
- Same applies to **evaluation metrics** and **methods**

OVERFITTING ON A GRAND SCALE

What can we do?

- Do improvements help with downstream applications?
  - **Extrinsic** evaluation
- No **metric** tells the full story
- Compare models on a range of
  - tasks
  - test sets (domains, languages, text types, . . .)
  - metrics
- Error analysis

SUMMARY

- Evaluation important for:
  - Public review
  - Internal review, quantification of improvements
- Unbiased comparison of *models*, *data*, *methods*
- **Intrinsic** vs **extrinsic**
- **Shared tasks** and common test sets

SUMMARY

- Metrics:
  accuracy, *perplexity*, *P*, *R*, *F-score*
- **Baselines** & **ceilings**
- **Significance testing** in NLP
- Splitting test data: *training*, *test*, *development*, *cross-val*
- **Human evaluation**
- **Error analysis**: confusion matrices
- **Annotation** of GS data

READING MATERIAL

- Evaluation intro, P, R, F-score: *J&M3 4.7*
- Intrinsic/extrinsic eval, data split, perplexity: *J&M3 3.2*
- Examples of shared tasks:
  http://www.conll.org/2019-shared-task
- Significance testing:
  Hitchhiker's Guide to Testing Statistical Significance in NLP
- Confusion matrices: *J&M3 p484*

NEXT UP

After lunch: practical assignments in **BK107**

9:15 – 12:00	Lectures
12:00 – 13:15	Lunch
13:15 – ∼14:00	Introduction
14:00 – 16:00	Practical assignments

- Data annotation
- Inter-annotator agreement
- Computing evaluation metrics