Project planning & system evaluation

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Project timeline

Today	Workshop 1: Project planning & system eval
May 4	Due: Lit review (15%)
May 16	Workshop 2: Writing up & presenting your work
May 23	Due: Project milestone (10%)
May 25 & June 1	Due: Oral presentations (5%)
June 6	Due: Final project paper (30%)

Forming teams

- You can work in teams of size 1, 2, or 3, but ...
- We heartily encourage teams of 3!
- Collaboration is the norm in scientific research, and in engineering and product development
- You can just get a lot more done: build bigger systems, explore more alternative choices, ...
- Leverage Piazza to find teammates

Goals for today

- Get you thinking concretely about what you want to accomplish
- Identify productive steps you can take even if you're still deciding on a topic or approach
- Try to help you avoid common pitfalls for projects
- Emphasize the importance of planning for system evaluation *early*
- Start building momentum for the final project!!

Inspiration

It’s nice if you do a great job and earn an A on your final project, but let’s think bigger:

- Many important and influential ideas, insights, and algorithms began as class projects
- Getting the best research-oriented jobs will likely involve giving a job talk. Your project can be the basis for one
- You can help out the scientific community by supplying data, code, and results (including things that didn’t work!)

Inspiring past projects

See: https://cs224u.stanford.edu/restricted/past-final-projects/

- Semantic role labeling
- Unsupervised relation extraction
- Solving standardized test problems
- Humor detection
- Biomedical NER
- Sentiment analysis in political contexts
- Learning narrative schemas
- Supervised and unsupervised compositional semantics
- …

Don’t neglect topics from later in quarter (e.g. semantic parsing)!

Agenda

- Overview
- Lit review
- Data sources
- Project set-up & development
- Evaluation
- Dataset management
- Evaluation metrics
- Comparative evaluations
- Other aspects of evaluation
- Conclusion

The literature review

- A short (~6-page) single-spaced paper summarizing and synthesizing several papers in the area of your final project.
- Groups of one should review 5 papers; groups of two, 7 papers; and groups of three, 9 papers.
- Preferably fuel for the final project, but graded on its own terms.

The lit review: what to include

Tips on major things to include:

- General problem / task definition
- Concise summaries of the papers
- Compare & contrast approaches (most important!)
- Future work: what remains undone?

More details at the homepage [link]

Our hopes

- The lit review research suggests baselines and approaches.
- The lit review helps us understand your project goals.
- We’ll be able to suggest additional things to read.
- The prose itself can be modified for inclusion in your final paper.

Finding the literature

The relevant fields are extremely well-organized when it comes to collecting their papers and making them accessible:

- ACL Anthology: http://www.aclweb.org/anthology/
- ACL Anthology Searchbench: http://aclasb.dfki.de/
- ACM Digital Library: http://dl.acm.org/
- arXiv: http://arxiv.org/
- Google Scholar: http://scholar.google.com/

Best-first search algorithm

Until you get a core set of lit review papers:

1. Do a keyword search on the ACL Anthology
2. Download the papers that seem most relevant
3. Skim the abstracts, intros, & previous work sections
4. Identify papers that look relevant, appear often, & have lots of citations on Google Scholar
5. Download those papers
6. Return to step 3

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The importance of data

- Your investigation should be *empirical* — i.e., data-driven
- We are scientists!
  - Well, or engineers — either way, we're empiricists!
  - Not poets or philosophers :-)
- You're trying to solve a real problem
  - Need to verify that your solution solves real problem instances
- So evaluate the output of your system on real inputs
  - Realistic data, not toy data or artificial data
  - Ideally, plenty of it

Sources of data

Three strategies for obtaining data:

1. Find it (the easiest way!)
2. Create it (the laborious way)
3. Pay others to create it (the expensive way)

(Our discussion will focus primarily on labeled data for supervised learning, but applies to unlabeled data too.)

Finding datasets

Linguistic Data Consortium: http://www.ldc.upenn.edu/

- Very large and diverse archive
- Especially rich in annotated data
- Expensive (but often free for Stanford)

Other useful starting points:

- http://kevinchai.net/datasets
- https://datahub.io/dataset?tags=nlp
- http://research.microsoft.com/en-US/projects/data-science-initiative/datasets.aspx

Stanford Linguistics corpora

- We subscribe to the LDC and so have most of their data sets: https://linguistics.stanford.edu/resources/corpora/corpus-inventory
- To get access, follow the instructions at this page: https://linguistics.stanford.edu/resources/corpora/accessing-corpora
- When you write to the corpus TA, cc the CS224U course staff address. Don’t forget this step!
- Write from your Stanford address. That will help the corpus TA figure out who you are and how to grant you access.

Some NLU datasets (open web)

- Google Wikilinks corpus: http://www.iesl.cs.umass.edu/data/wiki-links
- MSR Entity Recognition and Disambiguation Challenge: http://web-ngram.research.microsoft.com/erd2014/Datasets.aspx
- Google Ngrams data: https://books.google.com/ngrams
- PPDB: The Paraphrase Database: http://www.cis.upenn.edu/~ccb/ppdb/
- WikiAnswers Paraphrase Corpus: http://knowitall.cs.washington.edu/paralex/
- The SemEval-2014 SICK dataset: http://alt.qcri.org/semeval2014/task1/
- The Stanford NLI Corpus: http://nlp.stanford.edu/projects/snli/
- Abstract Meaning Representation (AMR) corpora: http://amr.isi.edu/download.html
- Winograd schemas: http://www.cs.nyu.edu/faculty/davise/papers/WS.html
- WebQuestions (semantic parsing): http://nlp.stanford.edu/software/sempre/

More NLU datasets (open web)

- Wikipedia data dumps: http://en.wikipedia.org/wiki/Wikipedia:Database_download
- Stack Exchange data dumps: https://archive.org/details/stackexchange
- Switchboard Dialog Act Corpus: http://www.stanford.edu/~jurafsky/ws97/
- Pranav Anand & co.: http://people.ucsc.edu/~panand/data.php
  - Internet Argument Corpus
  - Annotated political TV ads
  - Focus of negation corpus
  - Persuasion corpus (blogs)
- Data Chris has made available as part of other courses and projects:
  - Extracting social meaning and sentiment: http://nasslli2012.christopherpotts.net
  - Computational pragmatics: http://compprag.christopherpotts.net
  - The Cards dialogue corpus: http://cardscorpus.christopherpotts.net

Some NLU datasets (on AFS)

Get access from the corpus TA, as described earlier:

- Nate Chambers’ de-duped and dependency parsed NYT section of Gigaword: /afs/ir/data/linguistic-data/GigawordNYT
- Some data sets from Chris:
  - /afs/ir/data/linguistic-data/mnt/mnt4/PottsCorpora
    README.txt, Twitter.tgz, imdb-english-combined.tgz, opentable-english-processed.zip
  - /afs/ir/data/linguistic-data/mnt/mnt9/PottsCorpora
    opposingviews, product-reviews, weblogs
- Twitter data collected and organized by Moritz (former CS224Uer!)
  /afs/ir/data/linguistic-data/mnt/mnt3/TwitterTopics/

Twitter API

- https://dev.twitter.com/
- To stream random current tweets into a local file:

  ```
  curl http://stream.twitter.com/1/statuses/sample.json -uUSER:PASS
  ```

  I think this will deliver ≈7 million tweets/day.
- But Twitter data requires *extensive* pre-processing:
  - Filter heuristically by language (don't rely only on "lang" field)
  - Filter spam based on tweet structure (spam warnings: too many hashtags, too many usernames, too many links)
  - Handle retweets in a way that makes sense given your goals

Other APIs

- Kiva (micro-loans): http://build.kiva.org/
- eBay: http://developer.ebay.com/common/api/
- Yelp: http://www.yelp.com/developers/documentation
- Stack Exchange: http://api.stackexchange.com/
- Reddit: https://www.reddit.com/dev/api

Scraping

- Link structure is often regular (reflecting database structure)
- If you figure out the structure, you can often get lots of data!
- Once you have local copies of the pages:
  - Beautiful Soup (Python) is a powerful tool for parsing DOMs
  - Readability offers an API for extracting text from webpages
- Use rate limiting / request throttling !!!!!
- Read site policies! Be a good citizen! Don't get yourself (or your school) banned! Don't go to jail! You will not like it.
- For more on crawler etiquette, see Manning et al. 2009 (http://nlp.stanford.edu/IR-book/)

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Project set-up

Now that you’ve got your dataset more or less finalized, you can start building stuff and doing experiments!

Data management

- It will pay to get your data into an easy-to-use form and write general code for reading it.
- If your dataset is really large, considering putting it in a database or indexing it, so that you don’t lose a lot of development time iterating through it.

Automatic annotation tools

- If you need additional structure — POS tags, named-entity tags, parses, etc. — add it now.

- The Stanford NLP group has released lots of software for doing this: http://nlp.stanford.edu/software/index.shtml

- Can be used as libraries in Java/Scala.
  Or, can be used from the command-line.

- Check out CoreNLP in particular — amazing!

Conceptualizing your task

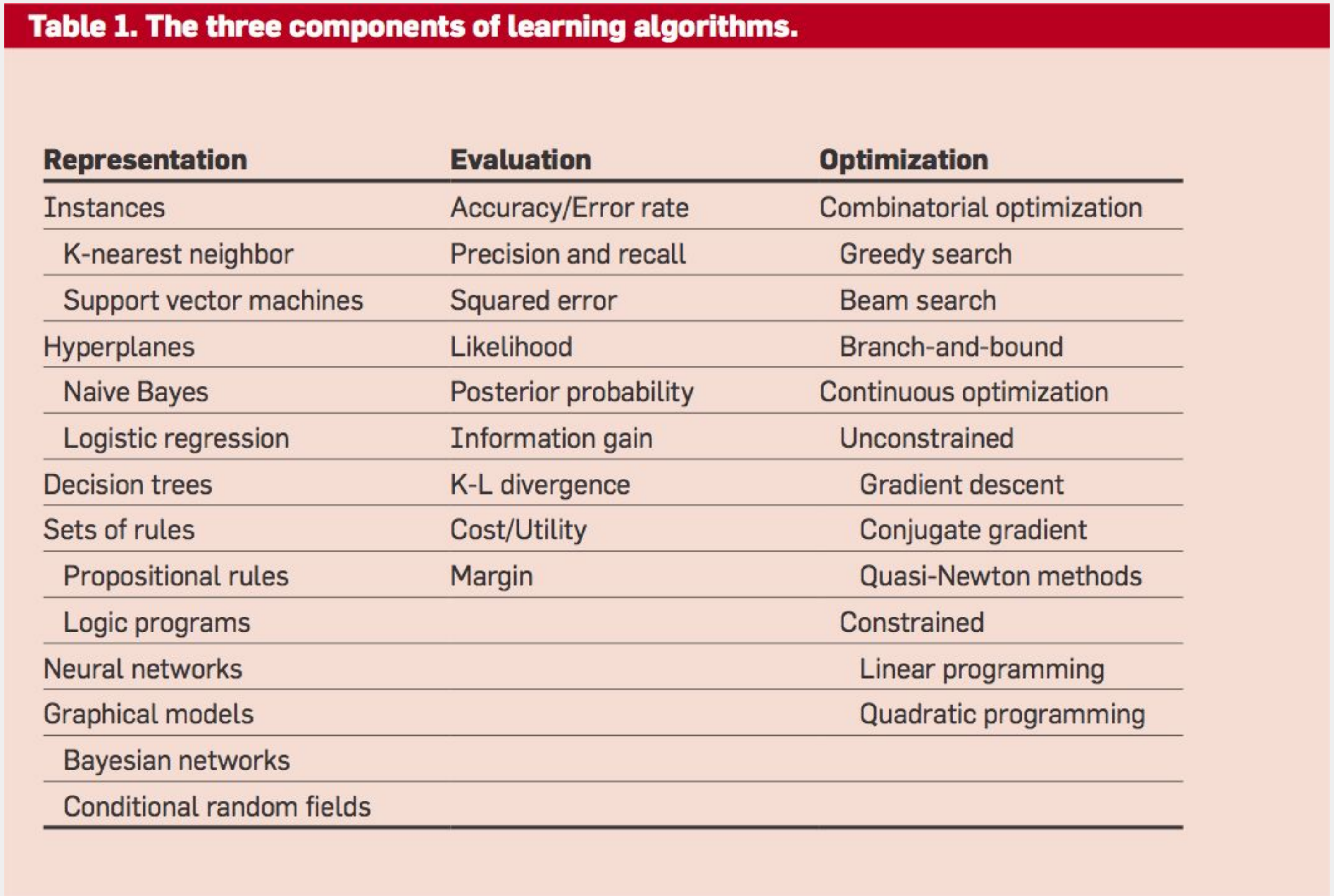


Table 1. The three components of learning algorithms.

Representation	Evaluation	Optimization
Instances	Accuracy/Error rate	Combinatorial optimization
K-nearest neighbor	Precision and recall	Greedy search
Support vector machines	Squared error	Beam search
Hyperplanes	Likelihood	Branch-and-bound
Naive Bayes	Posterior probability	Continuous optimization
Logistic regression	Information gain	Unconstrained
Decision trees	K-L divergence	Gradient descent
Sets of rules	Cost/Utility	Conjugate gradient
Propositional rules	Margin	Quasi-Newton methods
Logic programs		Constrained
Neural networks		Linear programming
Graphical models		Quadratic programming
Bayesian networks		
Conditional random fields		

Domingos 2012

Off-the-shelf modeling tools

While there’s some value in implementing algorithms yourself, it’s labor intensive and could seriously delay your project. We advise using existing tools whenever possible:

- Stanford Classifier (Java): http://nlp.stanford.edu/software/classifier.shtml
- Stanford Topic Modeling Toolbox (Scala): http://nlp.stanford.edu/software/tmt/tmt-0.4/
- MALLET (Java): http://mallet.cs.umass.edu/
- FACTORIE (Scala): http://factorie.cs.umass.edu/
- LingPipe (Java): http://alias-i.com/lingpipe/
- NLTK (Python): http://nltk.org/
- Gensim (Python): http://radimrehurek.com/gensim/
- GATE (Java): http://gate.ac.uk/
- scikits.learn (Python): http://scikit-learn.org/
- Lucene (Java): http://lucene.apache.org/core/

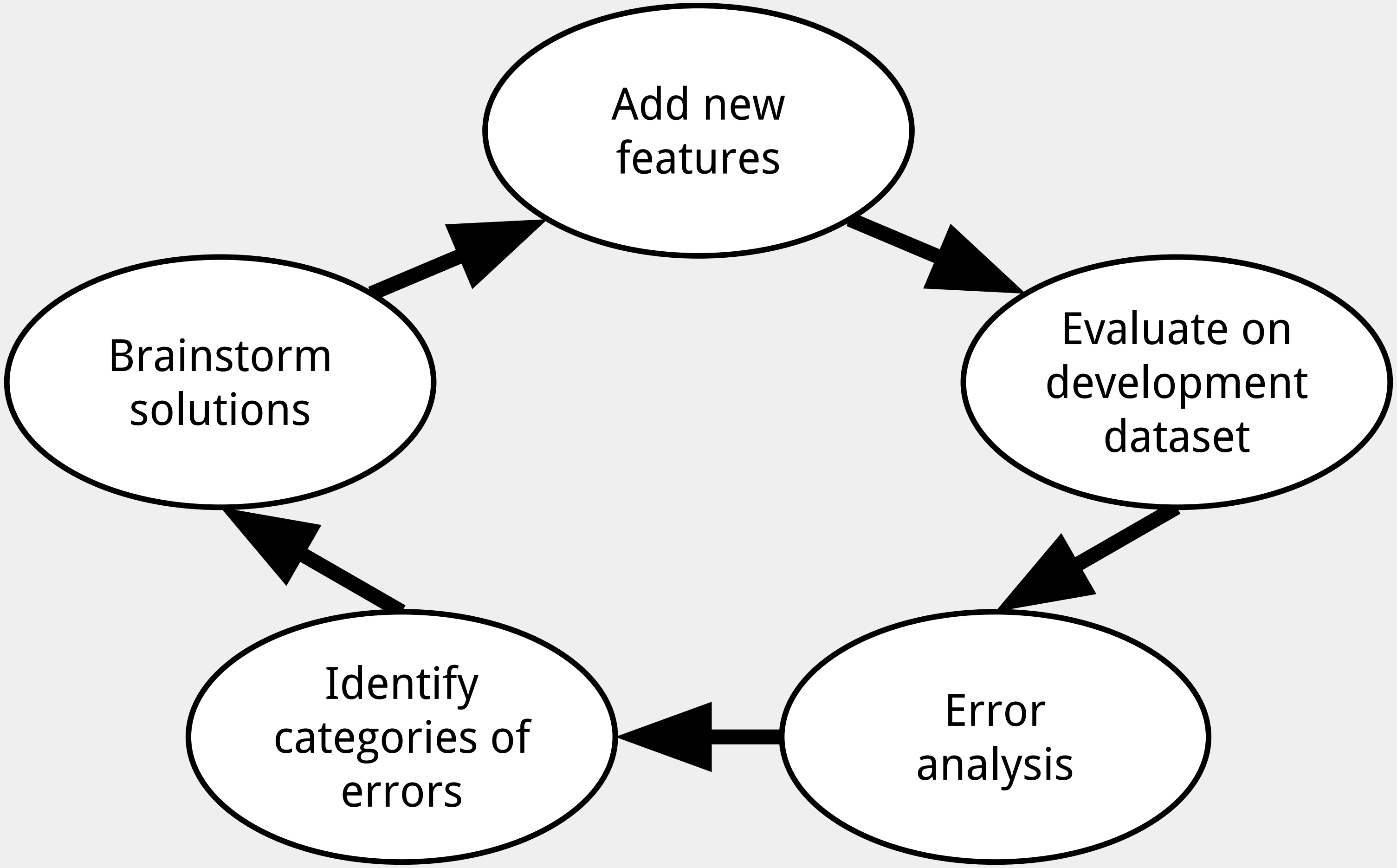
Iterative development

Launch & iterate!

- Get a baseline system running on real data ASAP
- Implement an evaluation — ideally, an automatic one, but could be more informal if necessary
- Hill-climb on your objective function
- Focus on feature engineering (next slide)

Goal: research as an “anytime” algorithm: have some results to show at every stage

The feature engineering cycle


Add new features
Evaluate on development dataset
Error analysis
Identify categories of errors
Brainstorm solutions

Focus on feature engineering

- Finding informative features matters more than choice of classification algorithm

  Domingos (2012:84): “At the end of the day, some machine learning projects succeed and some fail. What makes the difference? Easily the most important factor is the features used.”

- Do error analysis and let errors suggest new features!
- Look for clever ways to exploit new data sources
- Consider ways to combine multiple sources of information

More development tips

- Construct a tiny toy dataset for development
  - Facilitates understanding model behavior, finding bugs
- Consider ensemble methods
  - Develop multiple models with complementary expertise
  - Combine via max/min/mean/sum, voting, meta-classifier, ...
- Grid search in parameter space can be useful
  - Esp. for “hyperparameters”
  - Esp. when parameters are few and evaluation is fast
  - A kind of informal machine learning

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Why does evaluation matter?

In your final project, you will have:

- Identified a problem
- Explained why the problem matters
- Examined existing solutions, and found them wanting
- Proposed a new solution, and described its implementation

So the key question will be:

- Did you solve the problem?

The answer need not be yes, but the question must be addressed!

Who is it for?

Evaluation matters for many reasons, and for multiple parties:

- For future researchers
  - Should I adopt the methods used in this paper?
  - Is there an opportunity for further gains in this area?
- For reviewers
  - Does this paper make a useful contribution to the field?
- For yourself
  - Should I use method/data/classifier/... A or B?
  - What's the optimal value for parameter X?
  - What features should I add to my feature representation?
  - How should I allocate my remaining time and energy?

The role of data in evaluation

- Evaluation should be *empirical* — i.e., data-driven
- We are scientists!
  - Well, or engineers — either way, we're empiricists!
  - Not some hippie tree-hugging philosophers or poets
- You're trying to solve a real problem
  - Need to verify that your solution solves real problem instances
- So evaluate the output of your system on real inputs
  - Realistic data, not toy data or artificial data
  - Ideally, plenty of it

Kinds of evaluation

Quantitative	vs.	Qualitative
Automatic	vs.	Manual
Intrinsic	vs.	Extrinsic
Formative	vs.	Summative

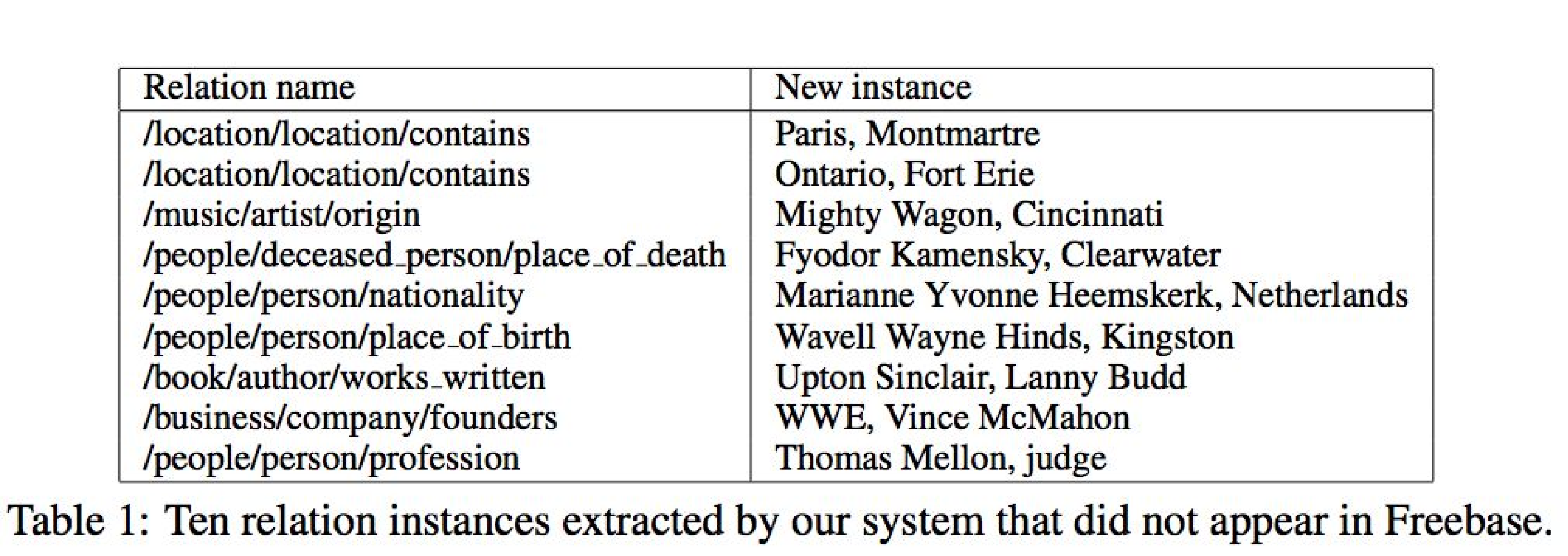
Quantitative vs. qualitative

- Quantitative evaluations should be primary
  - Evaluation metrics — *much* more below
  - Tables & graphs & charts, oh my!

- But qualitative evaluations are useful too!
  - Examples of system outputs
  - Error analysis
  - Visualizations
  - Interactive demos
    - A great way to gain visibility and impact for your work
    - Examples: OpenIE (relation extraction), Deeply Moving (sentiment)

- A tremendous aid to your readers' understanding!

Examples of system outputs

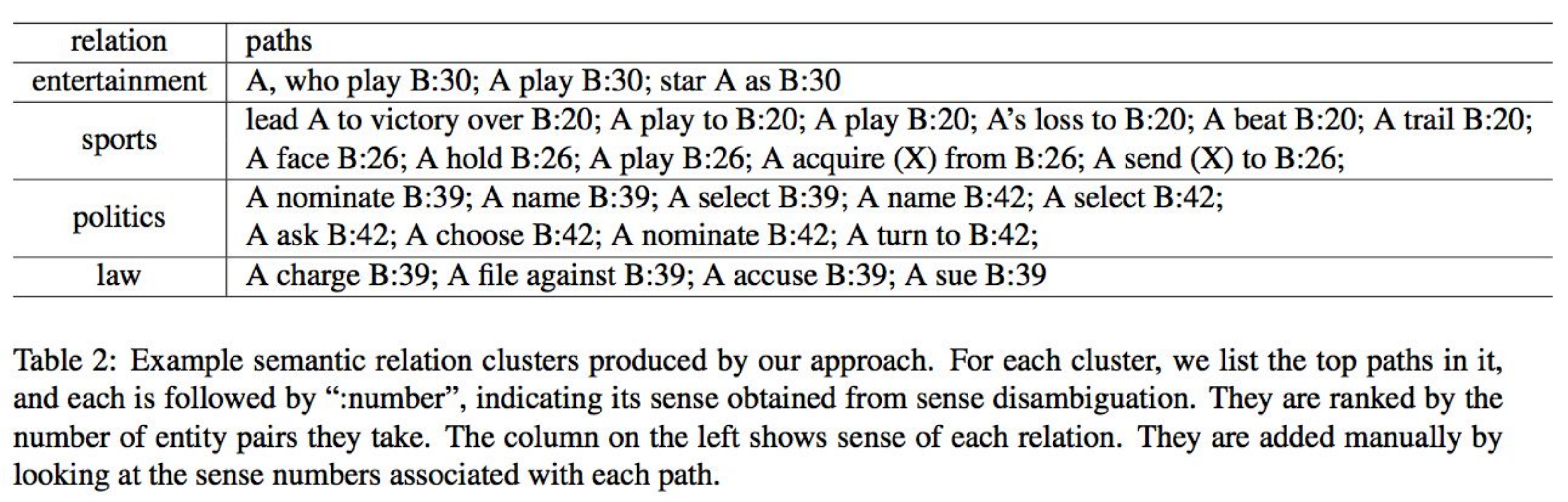


Relation name	New instance
/location/location/contains	Paris, Montmartre
/location/location/contains	Ontario, Fort Erie
/music/artist/origin	Mighty Wagon, Cincinnati
/people/deceased_person/place_of_death	Fyodor Kamensky, Clearwater
/people/person/nationality	Marianne Yvonne Heemskerk, Netherlands
/people/person/place_of_birth	Wavell Wayne Hinds, Kingston
/book/author/works_written	Upton Sinclair, Lanny Budd
/business/company/founders	WWE, Vince McMahon
/people/person/profession	Thomas Mellon, judge

Table 1: Ten relation instances extracted by our system that did not appear in Freebase.

from Mintz et al. 2009

Examples of system outputs

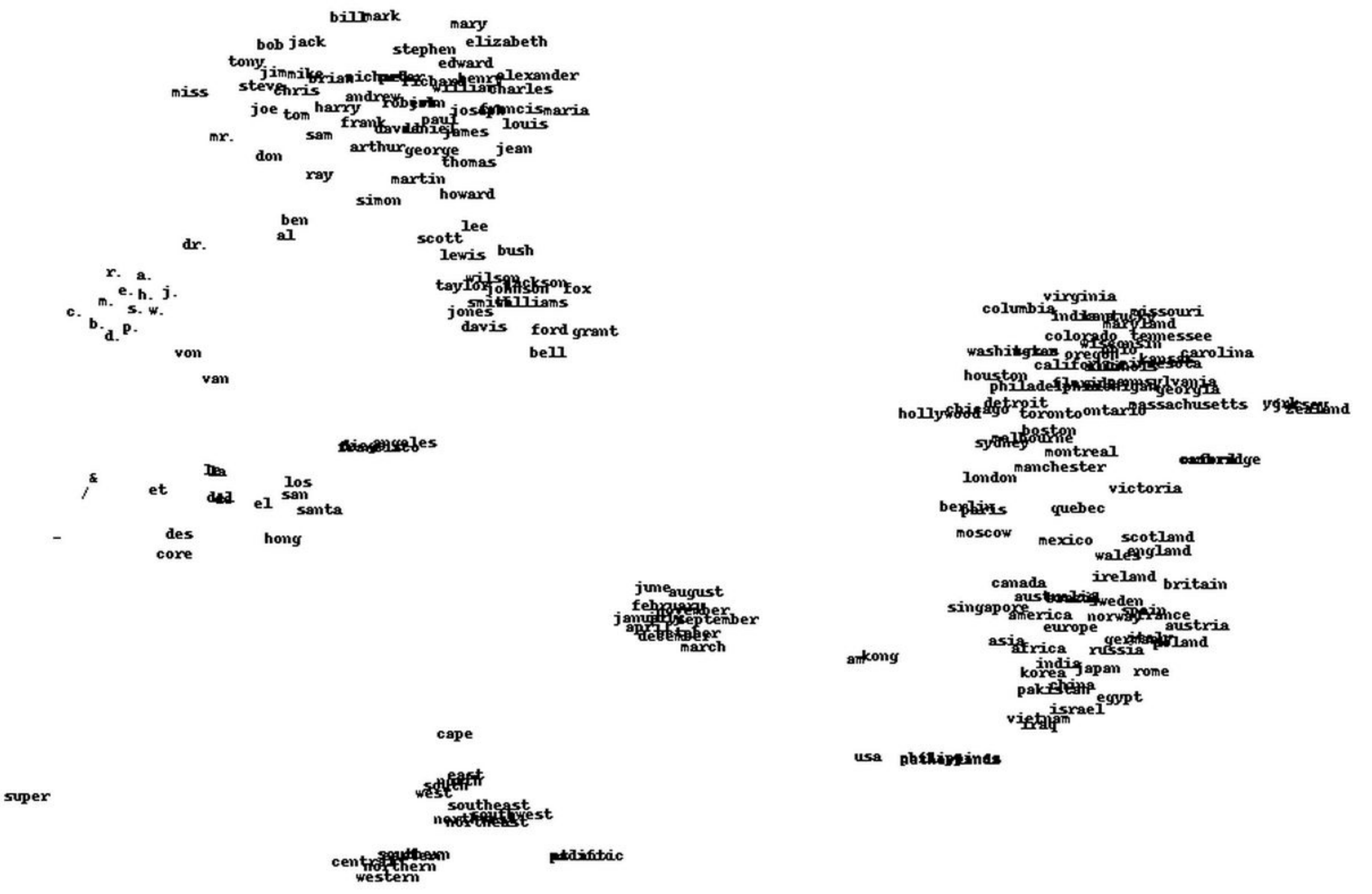


relation	paths
entertainment	A, who play B:30; A play B:30; star A as B:30
sports	lead A to victory over B:20; A play to B:20; A play B:20; A's loss to B:20; A beat B:20; A trail B:20; A face B:26; A hold B:26; A play B:26; A acquire (X) from B:26; A send (X) to B:26;
politics	A nominate B:39; A name B:39; A select B:39; A name B:42; A select B:42; A ask B:42; A choose B:42; A nominate B:42; A turn to B:42;
law	A charge B:39; A file against B:39; A accuse B:39; A sue B:39

Table 2: Example semantic relation clusters produced by our approach. For each cluster, we list the top paths in it, and each is followed by ":number", indicating its sense obtained from sense disambiguation. They are ranked by the number of entity pairs they take. The column on the left shows sense of each relation. They are added manually by looking at the sense numbers associated with each path.

from Yao et al. 2012

Example of visualization



from Joseph Turian

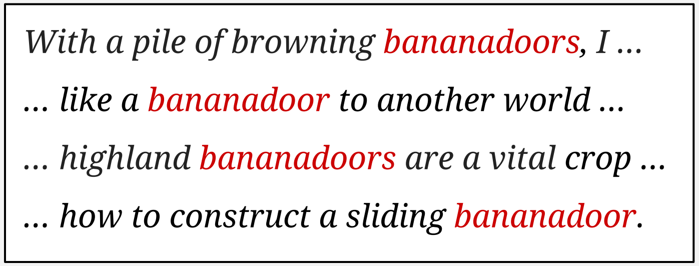
Automatic vs. manual evaluation

- Automatic evaluation
  - Typically: compare system outputs to some “gold standard”
  - Pro: cheap, fast
  - Pro: objective, reproducible
  - Con: may not reflect end-user quality
  - Especially useful during development (formative evaluation)
- Manual evaluation
  - Generate system outputs, have humans assess them
  - Pro: directly assesses real-world utility
  - Con: expensive, slow
  - Con: subjective, inconsistent
  - Most useful in final assessment (summative evaluation)

Automatic evaluation

- Automatic evaluation against human-annotated data
  - But human-annotated data is not available for many tasks
  - Even when it is, quantities are often rather limited

- Automatic evaluation against synthetic data
  - Example: pseudowords (*bananadoor*) in WSD
  - Example: cloze (completion) experiments
    - Chambers & Jurafsky 2008; Busch, Colgrove, & Neidert 2012
  - Pro: virtually infinite quantities of data
  - Con: lack of realism

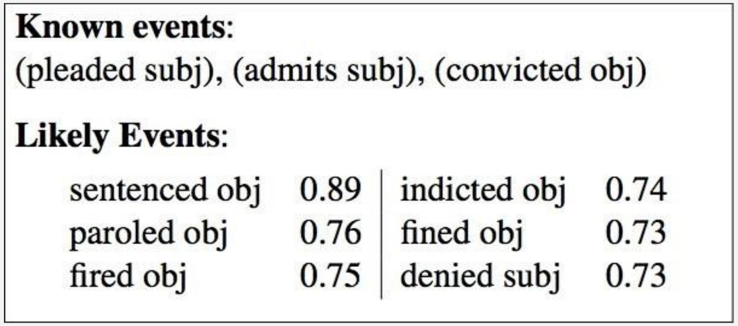


With a pile of browning bananadoors, I …

… like a bananadoor to another world …

… highland bananadoors are a vital crop …

… how to construct a sliding bananadoor.



Known events:
(pleaded subj), (admits subj), (convicted obj)

Likely Events:

sentenced obj	0.89	indicted obj	0.74
paroled obj	0.76	fined obj	0.73
fired obj	0.75	denied subj	0.73

Manual evaluation

- Generate system outputs, have humans evaluate them
- Pros: direct assessment of real-world utility
- Cons: expensive, slow, subjective, inconsistent
- But sometimes unavoidable! (Why?)
- Example: cluster intrusion in Yao et al. 2012
- Example: Banko et al. 2008

Intrinsic vs. extrinsic evaluation

- Intrinsic (*in vitro*, task-independent) evaluation
  - Compare system outputs to some ground truth or gold standard
- Extrinsic (*in vivo*, task-based, end-to-end) evaluation
  - Evaluate impact on performance of a larger system of which your model is a component
  - Pushes the problem back — need way to evaluate larger system
  - Pro: a more direct assessment of “real-world” quality
  - Con: often very cumbersome and time-consuming
  - Con: real gains may not be reflected in extrinsic evaluation
- Example from automatic summarization
  - Intrinsic: do summaries resemble human-generated summaries?
  - Extrinsic: do summaries help humans gather facts quicker?

Formative vs. summative evaluation

When the cook tastes the soup, that's formative;
when the customer tastes the soup, that's summative.

- Formative evaluation: guiding further investigations
  - Typically: lightweight, automatic, intrinsic
  - Compare design option A to option B
  - Tune parameters: smoothing, weighting, learning rate

- Summative evaluation: reporting results
  - Compare your approach to previous approaches
  - Compare different variants of your approach

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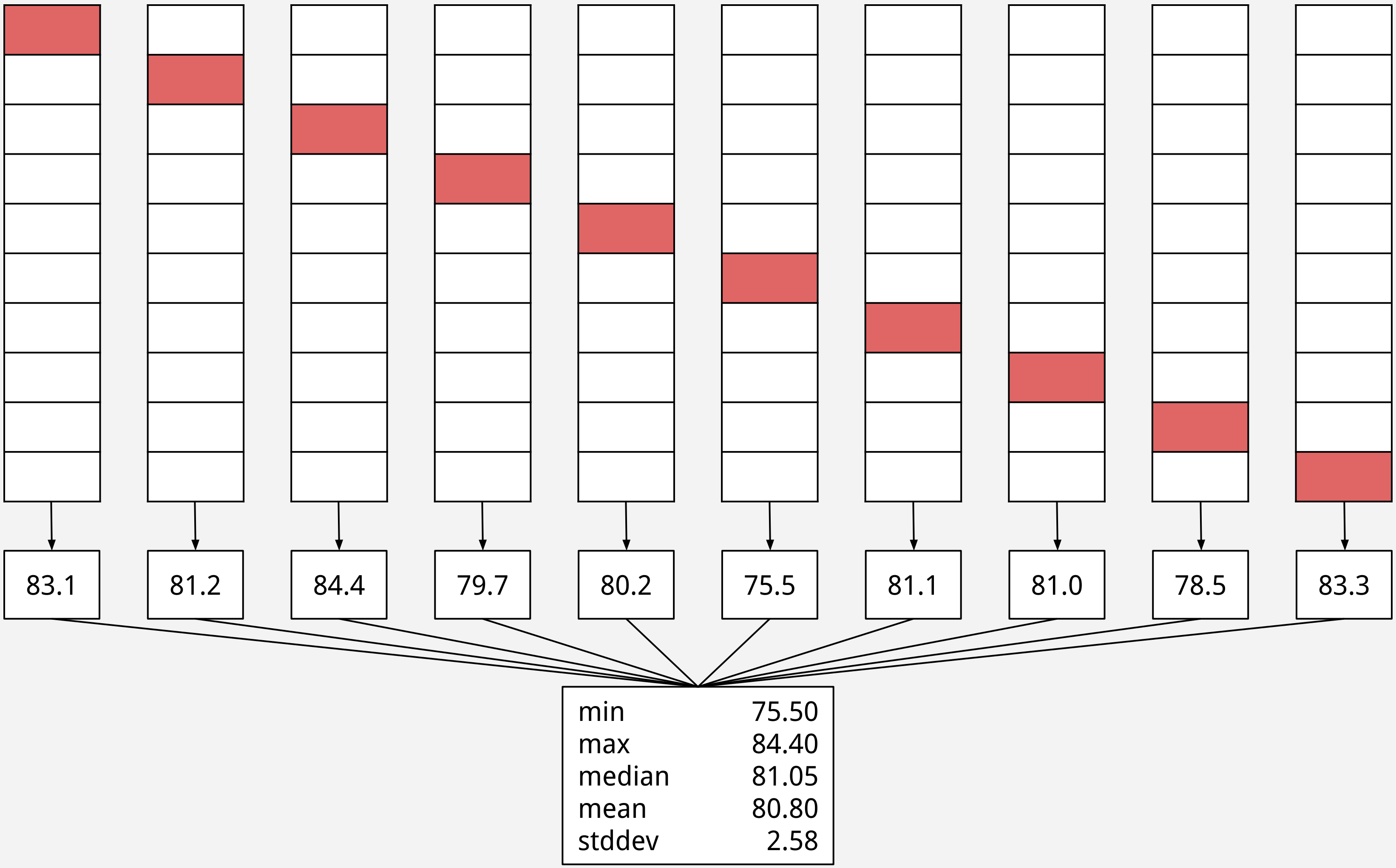
The train/test split

- Evaluations on training data overestimate real performance!
  - Need to test model's ability to *generalize*, not just memorize
  - But testing on training data can still be useful — how?
- So, sequester test data, use *only* for summative evaluation
  - Typically, set aside 10% or 20% of all data for final test set
  - If you're using a standard dataset, the split is often predefined
  - Don't evaluate on it until the very end! Don't peek!
- Beware of subtle ways that test data can get tainted
  - Using same test data in repeated experiments
  - "Community overfitting", e.g. on PTB parsing
  - E.g., matching items to users: partition on *users*, not matches

Development data

- Also known as “devtest” or “validation” data
- Used as test data during formative evaluations
  - Keep *real* test data pure until summative evaluation
- Useful for selecting (discrete) design options
  - Which categories of features to activate
  - Choice of classification (or clustering) algorithm
  - VSMs: choice of distance metric, normalization method, ...
- Useful for tuning (continuous) hyperparameters
  - Smoothing / regularization parameters
  - Combination weights in ensemble systems
  - Learning rates, search parameters

10-fold cross-validation (10CV)



min	75.50
max	84.40
median	81.05
mean	80.80
stddev	2.58

k-fold cross-validation

- Pros
  - Make better use of limited data
  - Less vulnerable to quirks of train/test split
  - Can estimate variance (etc.) of results
  - Enables crude assessment of statistical significance
- Cons
  - Slower (in proportion to k)
  - Doesn’t keep test data “pure” (if used in development)
- LOOCV = leave-one-out cross-validation
  - Increase k to the limit: the total number of instances
  - Magnifies both pros and cons

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Evaluation metrics

- An evaluation metric is a function: model × data → $\mathbb{R}$
- Can involve both manual and automatic elements
- Can serve as an objective function during development
  - For formative evaluations, identify *one* metric as primary
  - Known as “figure of merit”
  - Use it to guide design choices, tune hyperparameters
- You may use standard metrics, or design your own
  - Using standard metrics facilitates comparisons to prior work
  - But new problems may require new evaluation metrics
  - Either way, have good *reasons* for your choice

Evaluation metrics

Classification problems

- Contingency tables
- Confusion matrices
- Accuracy
- Precision & recall
- F-measure
- AUC (area under ROC curve)
- Sensitivity & specificity
- PPV & NPV (+/– predictive value)
- MCC (Matthews corr. coeff.)

Clustering problems

- Pairwise metrics
- B^3 metrics
- Intrusion tasks

Regression problems

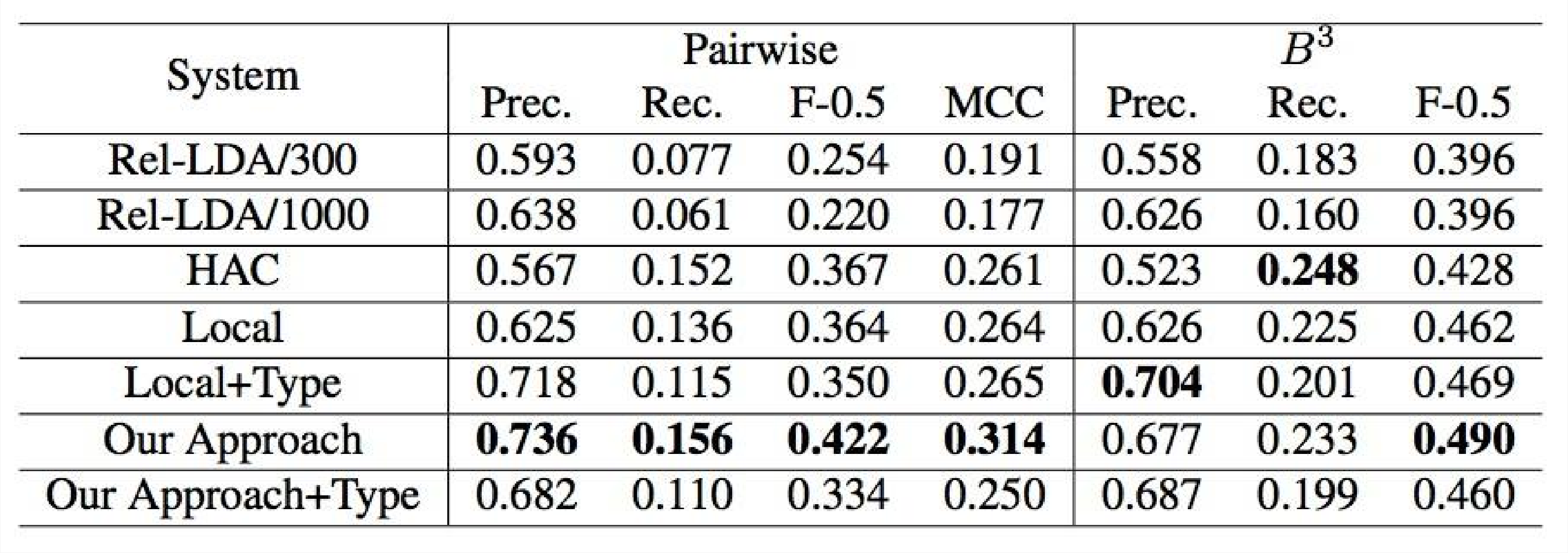
- Pearson’s R
- Mean squared error

Ranking problems

- Spearman’s rho
- Kendall’s tau
- Mean reciprocal rank

Example: evaluation metrics

Evaluation metrics are the *columns* of your main results table:



System	Pairwise				B^3		
	Prec.	Rec.	F-0.5	MCC	Prec.	Rec.	F-0.5
Rel-LDA/300	0.593	0.077	0.254	0.191	0.558	0.183	0.396
Rel-LDA/1000	0.638	0.061	0.220	0.177	0.626	0.160	0.396
HAC	0.567	0.152	0.367	0.261	0.523	**0.248**	0.428
Local	0.625	0.136	0.364	0.264	0.626	0.225	0.462
Local+Type	0.718	0.115	0.350	0.265	**0.704**	0.201	0.469
Our Approach	**0.736**	**0.156**	**0.422**	**0.314**	0.677	0.233	**0.490**
Our Approach+Type	0.682	0.110	0.334	0.250	0.687	0.199	0.460

from Yao et al. 2012

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Comparative evaluation

- Say your model scores 77% on your chosen evaluation metric
- *Is that good? Is it bad?*
- You (& your readers) can't know unless you make comparisons
  - Baselines
  - Upper bounds
  - Previous work
  - Different variants of your model
- Comparisons are the *rows* of your main results table
  - Evaluation metrics are the columns
- Comparisons demand statistical significance testing!

Baselines

- 77% doesn’t look so good if a blindfolded mule can get 73%
- Results without baseline comparisons are meaningless
- Weak baselines: performance of zero-knowledge systems
  - Systems which use no information about the specific instance
  - Example: random guessing models
  - Example: most-frequent class (MFC) models
- Strong baselines: performance of easily-implemented systems
  - Systems which can be implemented in an hour or less
  - Sentiment example: hand-crafted lexicon with +1/–1 weights
  - NLI example: bag-of-words

Upper bounds

- 77% doesn't look so bad if a even human expert gets only 83%
- *Plausible, defensible* upper bounds can flatter your results
- Human performance is often taken as an upper bound
  - Or inter-annotator agreement (for subjective labels)
  - (BTW, if you annotate your own data, report the kappa statistic)
  - If humans agree on only 83%, how can machines ever do better?
  - But in some tasks, machines outperform humans! (Ott et al. 2011)
- Also useful: oracle experiments
  - Supply gold output for some component of pipeline (e.g., parser)
  - Let algorithm access some information it wouldn't usually have
  - Can illuminate the system's operation, strengths & weaknesses

Comparisons to previous work

- Desirable, but not always possible — you may be a pioneer!
- Easy: same problem, same test data, same evaluation metric
  - Just copy results from previous work into your results table
  - The norm in tasks with standard data sets: ACE, Geo880, RTE, ...
- Harder: same problem, but different data, or different metric
  - Maybe you can obtain their code, and evaluate in your setup?
  - Maybe you can reimplement their system? Or an approximation?
- Hardest: new problem, new data set
  - Example: double entendre identification (Kiddon & Brun 2011)
  - Make your data set publicly available!
  - Let future researchers can compare to *you*

Different variants of your model

- Helps to shed light your model’s strengths & weaknesses
- Lots of elements can be varied
  - Quantity, corpus, or genre of training data
  - Active feature categories
  - Classifier type or clustering algorithm
  - VSMs: distance metric, normalization method, ...
  - Smoothing / regularization parameters

Relative improvements

- It may be preferable to express improvements in *relative* terms
  - Say baseline was 60%, and your model achieved 75%
  - Absolute gain: 15%
  - Relative improvement: 25%
  - Relative error reduction: 37.5%

- Can be more informative (as well as more flattering!)
  - Previous work: 92.1%
  - Your model: 92.9%
  - Absolute gain: 0.8%   (yawn)
  - Relative error reduction: 10.1%   (wow!)

Statistical significance testing

- Pet peeve: small gains reported as fact w/o significance testing
  - "... outperforms previous approaches ..."
  - "... demonstrates that word features help ..."
- How likely is the gain you observed, under the null hypothesis?
  - Namely: model is no better than baseline, and gain is due to chance
- Crude solution: estimate variance using 10CV, or "the bootstrap"
- Analytic methods: McNemar's paired test, many others ...
- Monte Carlo methods: approximate randomization
  - Easy to implement, reliable, principled
  - Highly recommended reading: http://masanjin.net/sigtest.pdf

Significant skepticism

Lately there's been some healthy skepticism about the value of p-values. For example:

http://www.nature.com/news/scientific-method-statistical-errors-1.14700

Lesson: $p < 0.05$ may not be a reliable indicator of a truly significant result.

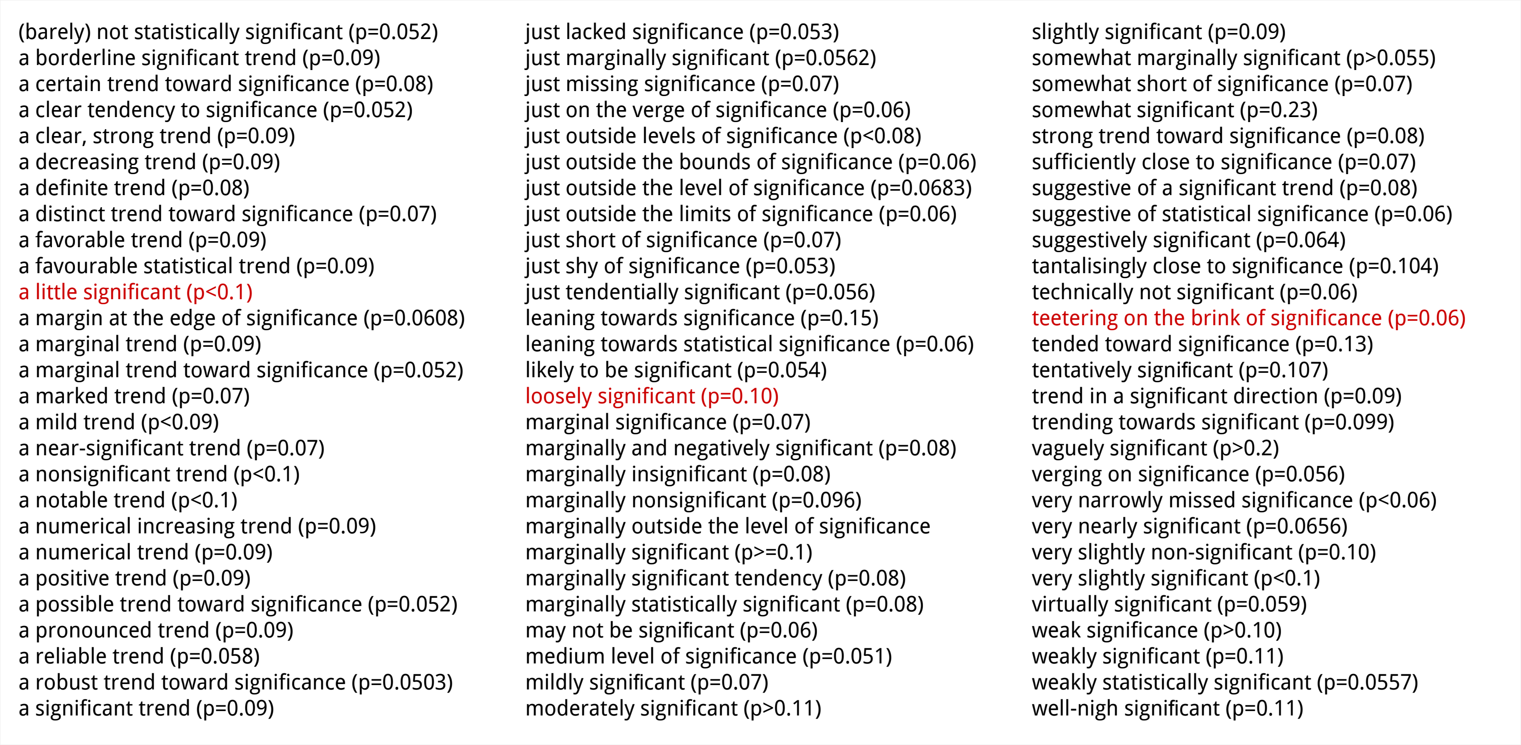
But $p > 0.05$ still means you haven't proven s---.

And you should still do significance testing!

Still not significant

If the result ain't significant, just admit it!

No weasel words!



(barely) not statistically significant (p=0.052)
a borderline significant trend (p=0.09)
a certain trend toward significance (p=0.08)
a clear tendency to significance (p=0.052)
a clear, strong trend (p=0.09)
a decreasing trend (p=0.09)
a definite trend (p=0.08)
a distinct trend toward significance (p=0.07)
a favorable trend (p=0.09)
a favourable statistical trend (p=0.09)
a little significant (p<0.1)
a margin at the edge of significance (p=0.0608)
a marginal trend (p=0.09)
a marginal trend toward significance (p=0.052)
a marked trend (p=0.07)
a mild trend (p<0.09)
a near-significant trend (p=0.07)
a nonsignificant trend (p<0.1)
a notable trend (p<0.1)
a numerical increasing trend (p=0.09)
a numerical trend (p=0.09)
a positive trend (p=0.09)
a possible trend toward significance (p=0.052)
a pronounced trend (p=0.09)
a reliable trend (p=0.058)
a robust trend toward significance (p=0.0503)
a significant trend (p=0.09)
just lacked significance (p=0.053)
just marginally significant (p=0.0562)
just missing significance (p=0.07)
just on the verge of significance (p=0.06)
just outside levels of significance (p<0.08)
just outside the bounds of significance (p=0.06)
just outside the level of significance (p=0.0683)
just outside the limits of significance (p=0.06)
just short of significance (p=0.07)
just shy of significance (p=0.053)
just tendentially significant (p=0.056)
leaning towards significance (p=0.15)
leaning towards statistical significance (p=0.06)
likely to be significant (p=0.054)
loosely significant (p=0.10)
marginal significance (p=0.07)
marginally and negatively significant (p=0.08)
marginally insignificant (p=0.08)
marginally nonsignificant (p=0.096)
marginally outside the level of significance
marginally significant (p>=0.1)
marginally significant tendency (p=0.08)
marginally statistically significant (p=0.08)
may not be significant (p=0.06)
medium level of significance (p=0.051)
mildly significant (p=0.07)
moderately significant (p>0.11)
slightly significant (p=0.09)
somewhat marginally significant (p>0.055)
somewhat short of significance (p=0.07)
somewhat significant (p=0.23)
strong trend toward significance (p=0.08)
sufficiently close to significance (p=0.07)
suggestive of a significant trend (p=0.08)
suggestive of statistical significance (p=0.06)
suggestively significant (p=0.064)
tantalisingly close to significance (p=0.104)
technically not significant (p=0.06)
teetering on the brink of significance (p=0.06)
tended toward significance (p=0.13)
tentatively significant (p=0.107)
trend in a significant direction (p=0.09)
trending towards significant (p=0.099)
vaguely significant (p>0.2)
verging on significance (p=0.056)
very narrowly missed significance (p<0.06)
very nearly significant (p=0.0656)
very slightly non-significant (p=0.10)
very slightly significant (p<0.1)
virtually significant (p=0.059)
weak significance (p>0.10)
weakly significant (p=0.11)
weakly statistically significant (p=0.0557)
well-nigh significant (p=0.11)

http://mchankins.wordpress.com/2013/04/21/still-not-significant-2/

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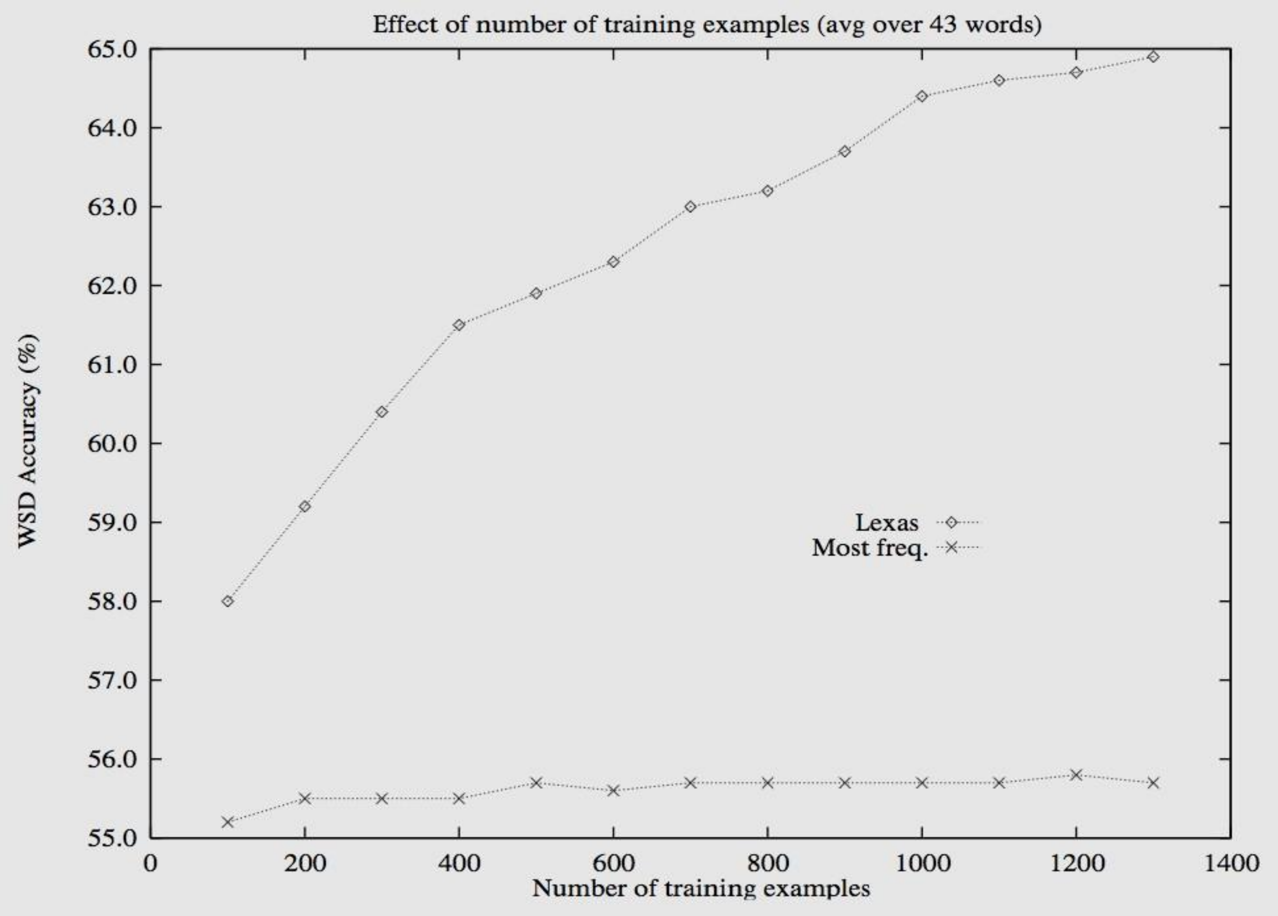
Learning curves

- Plot evaluation metric as function of amount of training data
- May include multiple variants of model (e.g. classifier types)
- Provides insight into learning properties of model
- Pop quiz: what does it mean if ...
  - ... the curve is flat and never climbs?
  - ... the curve climbs and doesn’t ever level off?
  - ... the curve climbs at first, but levels off quite soon?

Learning curve example

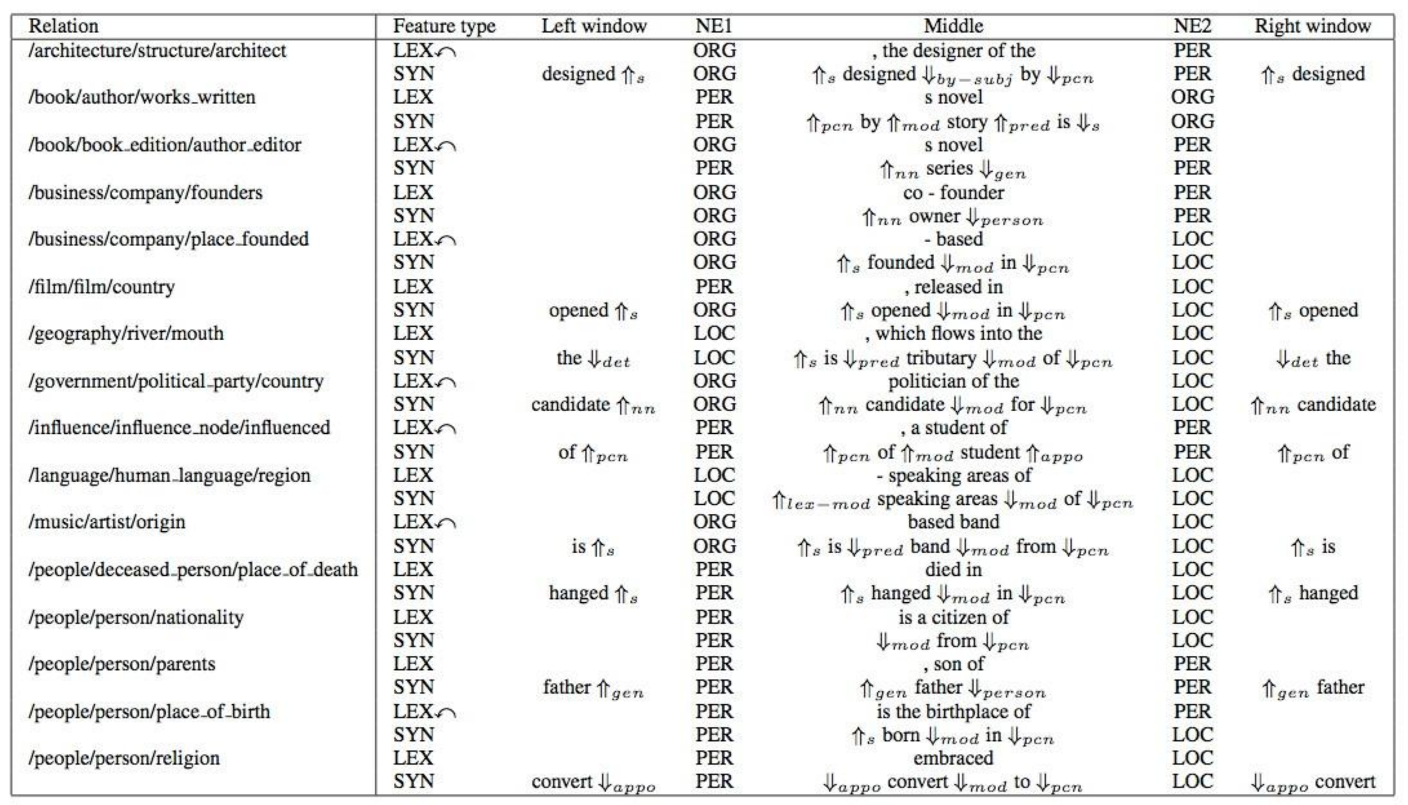


from Ng & Zelle 1997

Feature analysis

- Goal: understand which features are most informative
- Easy, but potentially misleading: list high-weight features
  - Implicitly assumes that features are independent
- Per-feature statistical measures
  - E.g., chi-square, information gain
  - Again, ignores potential feature interactions
- Ablation (or addition) tests
  - Progressively knock out (or add) (categories of) features
  - Do comparative evaluations at each step — often expensive!
- L1 regularization, Lasso, & other feature selection algorithms
  - Which features are selected? What are the regularization paths?

Example: high-weight features

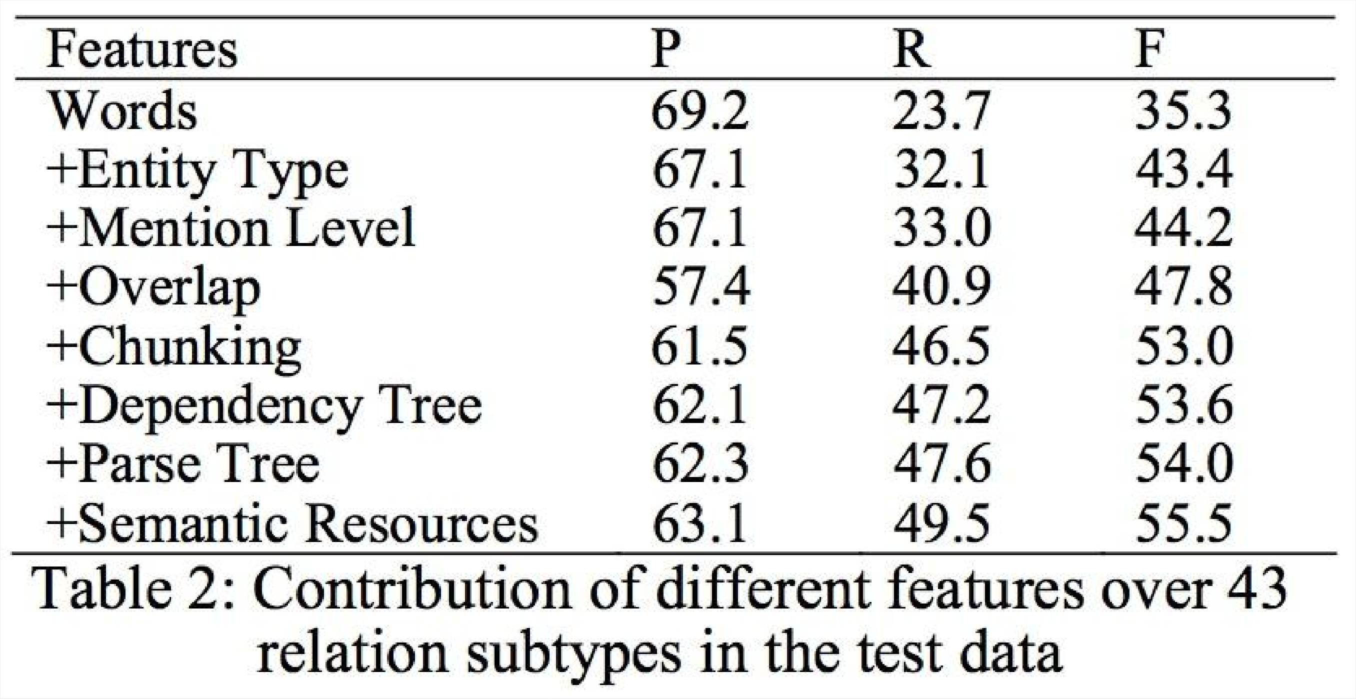


Relation	Feature type	Left window	NE1	Middle	NE2	Right window
/architecture/structure/architect	LEX$\curvearrowleft$		ORG	, the designer of the	PER	
	SYN	designed $\Uparrow_s$	ORG	$\Uparrow_s$ designed $\Downarrow_{by-subj}$ by $\Downarrow_{pcn}$	PER	$\Uparrow_s$ designed
/book/author/works_written	LEX		PER	s novel	ORG	
	SYN		PER	$\Uparrow_{pcn}$ by $\Uparrow_{mod}$ story $\Uparrow_{pred}$ is $\Downarrow_s$	ORG	
/book/book_edition/author_editor	LEX$\curvearrowleft$		ORG	s novel	PER	
	SYN		PER	$\Uparrow_{nn}$ series $\Downarrow_{gen}$	PER	
/business/company/founders	LEX		ORG	co - founder	PER	
	SYN		ORG	$\Uparrow_{nn}$ owner $\Downarrow_{person}$	PER	
/business/company/place_founded	LEX$\curvearrowleft$		ORG	- based	LOC	
	SYN		ORG	$\Uparrow_s$ founded $\Downarrow_{mod}$ in $\Downarrow_{pcn}$	LOC	
/film/film/country	LEX		PER	, released in	LOC	
	SYN	opened $\Uparrow_s$	ORG	$\Uparrow_s$ opened $\Downarrow_{mod}$ in $\Downarrow_{pcn}$	LOC	$\Uparrow_s$ opened
/geography/river/mouth	LEX		LOC	, which flows into the	LOC	
	SYN	the $\Downarrow_{det}$	LOC	$\Uparrow_s$ is $\Downarrow_{pred}$ tributary $\Downarrow_{mod}$ of $\Downarrow_{pcn}$	LOC	$\Downarrow_{det}$ the
/government/political_party/country	LEX$\curvearrowleft$		ORG	politician of the	LOC	
	SYN	candidate $\Uparrow_{nn}$	ORG	$\Uparrow_{nn}$ candidate $\Downarrow_{mod}$ for $\Downarrow_{pcn}$	LOC	$\Uparrow_{nn}$ candidate
/influence/influence_node/influenced	LEX$\curvearrowleft$		PER	, a student of	PER	
	SYN	of $\Uparrow_{pcn}$	PER	$\Uparrow_{pcn}$ of $\Uparrow_{mod}$ student $\Uparrow_{appo}$	PER	$\Uparrow_{pcn}$ of
/language/human_language/region	LEX		LOC	- speaking areas of	LOC	
	SYN		LOC	$\Uparrow_{lex-mod}$ speaking areas $\Downarrow_{mod}$ of $\Downarrow_{pcn}$	LOC	
/music/artist/origin	LEX$\curvearrowleft$		ORG	based band	LOC	
	SYN	is $\Uparrow_s$	ORG	$\Uparrow_s$ is $\Downarrow_{pred}$ band $\Downarrow_{mod}$ from $\Downarrow_{pcn}$	LOC	$\Uparrow_s$ is
/people/deceased_person/place_of_death	LEX		PER	died in	LOC	
	SYN	hanged $\Uparrow_s$	PER	$\Uparrow_s$ hanged $\Downarrow_{mod}$ in $\Downarrow_{pcn}$	LOC	$\Uparrow_s$ hanged
/people/person/nationality	LEX		PER	is a citizen of	LOC	
	SYN		PER	$\Downarrow_{mod}$ from $\Downarrow_{pcn}$	LOC	
/people/person/parents	LEX		PER	, son of	PER	
	SYN	father $\Uparrow_{gen}$	PER	$\Uparrow_{gen}$ father $\Downarrow_{person}$	PER	$\Uparrow_{gen}$ father
/people/person/place_of_birth	LEX$\curvearrowleft$		PER	is the birthplace of	PER	
	SYN		PER	$\Uparrow_s$ born $\Downarrow_{mod}$ in $\Downarrow_{pcn}$	LOC	
/people/person/religion	LEX		PER	embraced	LOC	
	SYN	convert $\Downarrow_{appo}$	PER	$\Downarrow_{appo}$ convert $\Downarrow_{mod}$ to $\Downarrow_{pcn}$	LOC	$\Downarrow_{appo}$ convert

Table 4: Examples of high-weight features for several relations. Key: SYN = syntactic feature; LEX = lexical feature; $\curvearrowleft$ = reversed; NE# = named entity tag of entity.

from Mintz et al. 2009

Example: feature addition tests



Features	P	R	F
Words	69.2	23.7	35.3
+Entity Type	67.1	32.1	43.4
+Mention Level	67.1	33.0	44.2
+Overlap	57.4	40.9	47.8
+Chunking	61.5	46.5	53.0
+Dependency Tree	62.1	47.2	53.6
+Parse Tree	62.3	47.6	54.0
+Semantic Resources	63.1	49.5	55.5

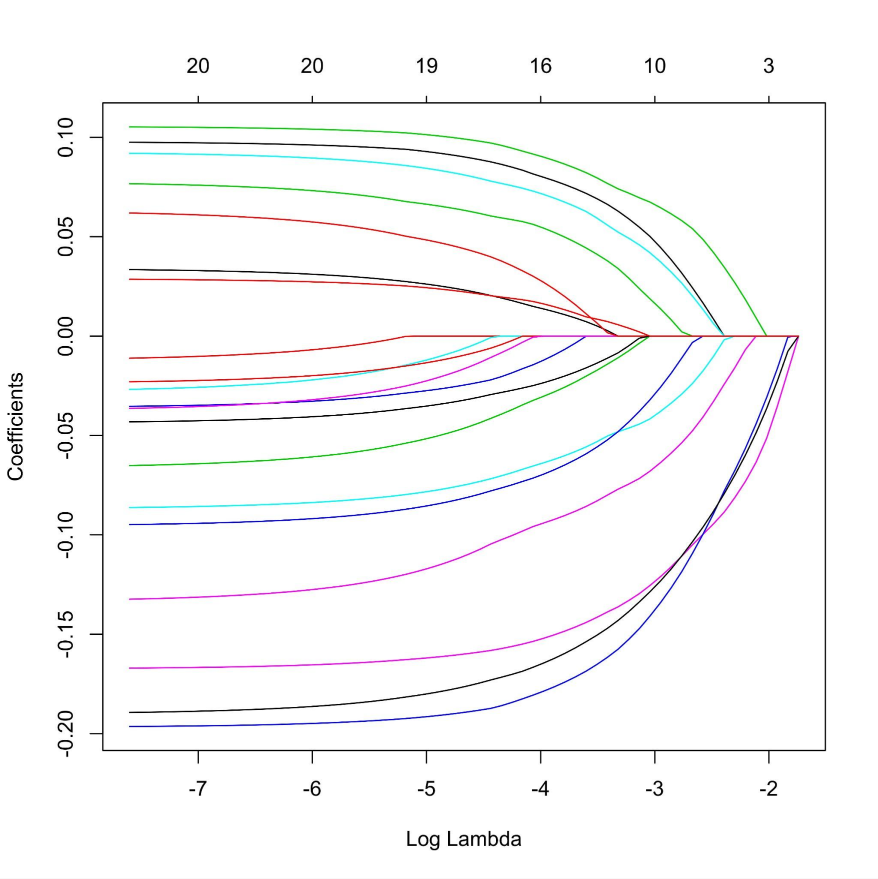
Table 2: Contribution of different features over 43 relation subtypes in the test data

from Zhou et al. 2005

Visualizations

- Helpful in making multiple formal and informal comparisons, identify overlooked relationships
- t-SNE for 2d visualization of high-dimensional data: http://homepage.tudelft.nl/19j49/t-SNE.html
- Gephi: http://gephi.org/
- Visualization tools from Jeff Heer's group: http://hci.stanford.edu/jheer/

Example: regularization paths

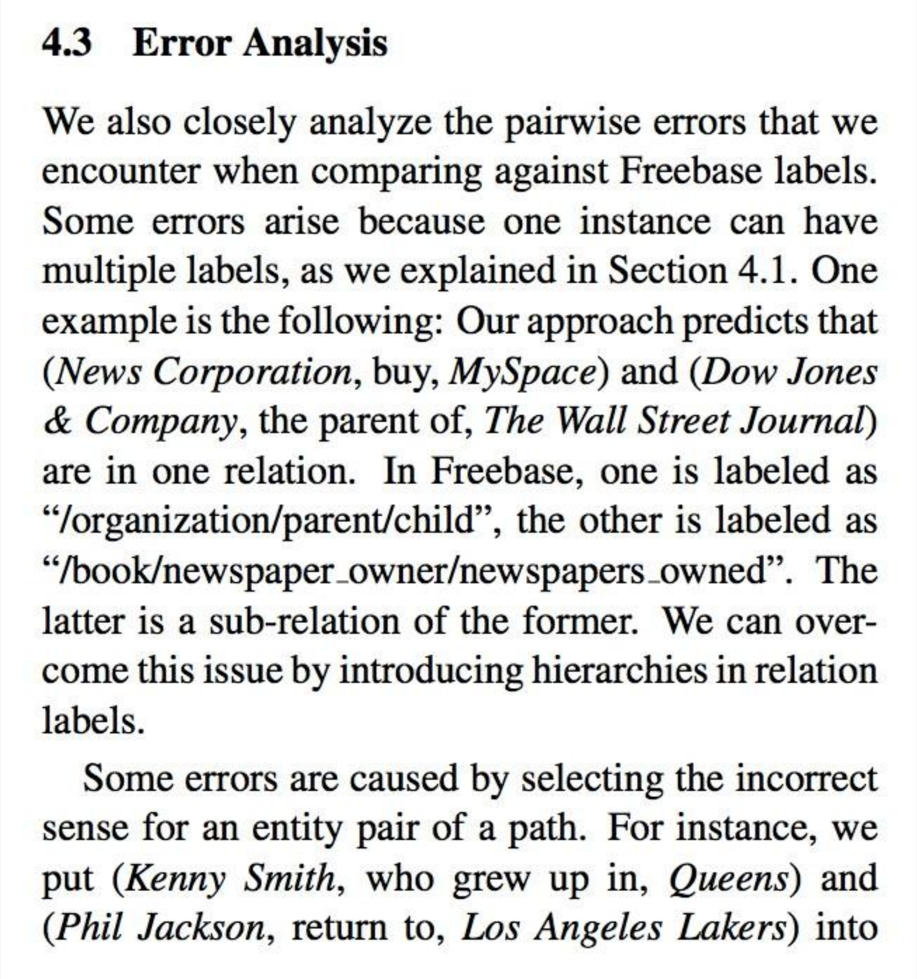


made using the glmnet package in R

Error analysis

- Analyze and categorize specific errors (on *dev* data, not test!)
- A form of *qualitative* evaluation — **yet indispensable!**
- During development (formative evaluation):
    - Examine individual mistakes, group into categories
    - Can be helpful to focus on FPs, FNs, common confusions
    - Brainstorm remedies for common categories of error
    - A key driver of iterative cycles of feature engineering
- In your report (summative evaluation):
    - Describe common categories of errors, exhibit specific examples
    - Aid the reader in understanding limitations of your approach
    - Highlight opportunities for future work

Error analysis example



4.3 Error Analysis

We also closely analyze the pairwise errors that we encounter when comparing against Freebase labels. Some errors arise because one instance can have multiple labels, as we explained in Section 4.1. One example is the following: Our approach predicts that (*News Corporation*, buy, *MySpace*) and (*Dow Jones & Company*, the parent of, *The Wall Street Journal*) are in one relation. In Freebase, one is labeled as "/organization/parent/child", the other is labeled as "/book/newspaper_owner/newspapers_owned". The latter is a sub-relation of the former. We can overcome this issue by introducing hierarchies in relation labels.

Some errors are caused by selecting the incorrect sense for an entity pair of a path. For instance, we put (*Kenny Smith*, who grew up in, *Queens*) and (*Phil Jackson*, return to, *Los Angeles Lakers*) into

from Yao et al. 2012

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Don’t fear negative results

Research is the process of going up alleys to see if they are blind.
— Marston Bates, American zoologist, 1906-1974

- Sometimes the results aren’t as good as you’d like
  - Sometimes you can’t show a statistically significant gain
  - Sometimes you can’t even beat the weak baseline :-(
- Your research work can still have value!
  - Especially if what you tried was a reasonable thing to try
  - Save future researchers from going up the same blind alleys
  - Worst case: error analysis is most valuable part of your paper
- Resist the temptation to optimize on test data
  - This is basically intellectual fraud

Plan for evaluation *early*

Evaluation should not be merely an afterthought;
it must be an integral part of designing a research project.

You can’t aim if you don’t have a target;
you can’t optimize if you don’t have an objective function.

First decide how to measure success;
then pursue it relentlessly!

Whoa, dude, that’s some serious Yoda sh

Game plan

- Form a team of 3 and choose a topic
- Survey previous work — lit review due May 4
- Identify data sources *soon*
- Leverage off-the-shelf tools where possible
- Launch & iterate — “anytime” research process
- Plan for evaluation early!

Appendix: data annotation

Annotating data

If you can’t find suitable annotated data, you might consider annotating your own data. But:

- The quantity will be small → harder to learn from
- Your evaluations will be less convincing — no comparison to prior work
- It’s a pain in the ass!
- You must not let this be a bottleneck!

Later we’ll discuss crowdsourcing, which is less risky (but more limited in what it can accomplish).

Setting up an annotation project

- Plan to have multiple annotators! (Enlist your friends.)
- Annotate a subset of the data yourself. This will reveal challenges and sources of ambiguity.
- Writing a detailed annotation manual will save you time in the long run, even if it delays the start of annotation.
- Consider a training phase for annotators, following by discussion.
- Consider whether your annotators should be allowed to collaborate and/or resolve differences among themselves.
- brat rapid annotation tool: http://brat.nlplab.org

Assessing annotation quality

- Cohen’s kappa is the standard measure of inter-annotator agreement in NLP. It works only where there are exactly two annotators and all of them did the same annotations.
- Fleiss’ kappa is suitable for situations in which there are multiple annotators, and there is no presumption that they all did the same examples.
- Both kinds of kappa assume the labels are unordered. Thus, they will be harsh/conservative for situations in which the categories are ordered.
- The central motivation behind the kappa measures is that they take into account the level of (dis)agreement that we can expect to see by chance. Measures like “percentage choosing the same category” do not include such a correction.

Sources of uncertainty

- Ambiguity and vagueness are part of what make natural languages powerful and flexible.
- However, this ensures that there will be uncertainty about which label to assign to certain examples.
- Annotators might speak different dialects, and thus have different linguistic intuitions.
- Such variation will be systematic and thus perhaps detectable.
- Some annotators are just better than others.

Pitfalls

- Annotation projects almost never succeed on the first attempt. This is why we don't really encourage you to start one now for the sake of your project.
- (Crowdsourcing situations are an exception to this, not because they succeed right way, but rather because they might take just a day from start to finish.)
- Annotation is time-consuming and expensive where experts are involved.
- Annotation is frustrating and taxing where the task is filled with uncertainty. Uncertainty is much harder to deal with than a simple challenge.

Crowdsourcing

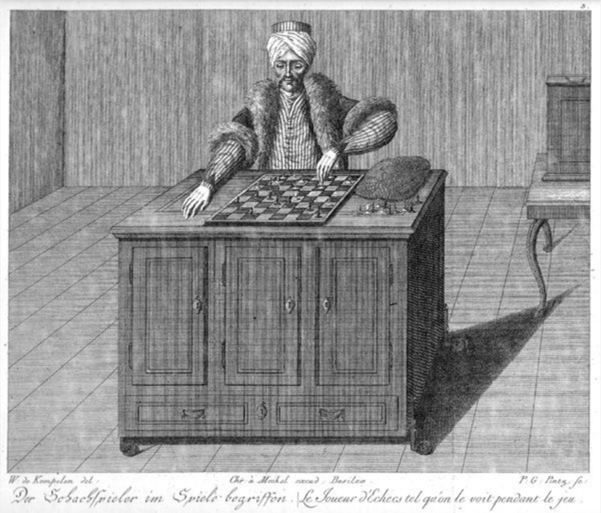
If ...

- You need new annotations
- You need a *ton* of annotations
- Your annotations can be done by non-experts

… crowdsourcing might provide what you need, provided that you go about it with care.

The original Mechanical Turk

Advertised as a chess-playing machine, but actually just a large box containing a human expert chess player.


W. de Kempelen del.
Chr. à Mechel excud. Basileæ.
P. G. Pintz. fc.
Der Schachſpieler im Spiele begriffen. Le Joueur d'Echecs tel qu'on le voit pendant le jeu.

http://en.wikipedia.org/wiki/The_Turk

So Amazon's choice of the name "Mechanical Turk" for its crowdsourcing platform is appropriate: humans just like you are doing the tasks,
so treat them as you would treat someone doing a favor for you.

Crowdsourcing platforms

There are several, including:

- Amazon Mechanical Turk: https://www.mturk.com/
- Crowdflower (handles quality control): http://crowdflower.com/
- oDesk (for expert work): https://www.odesk.com

Who turks?

http://waxy.org/2008/11/the_faces_of_mechanical_turk/

Papers

- Munro and Tily (2011): history of crowdsourcing for language technologies, along with assessment of the methods
- Crowd Scientist, a collection of slideshows highlighting diverse uses of crowdsourcing: http://www.crowdscientist.com/workshop/
- 2010 NAACL workshop on crowdsourcing: http://aclweb.org/anthology-new/W/W10/#0700
- Snow et al. (2008): early and influential crowdsourcing paper: crowdsourcing requires more annotators to reach the level of experts, but this can still be dramatically more economical
- Hsueh et al. (2009): strategies for managing the various sources of uncertainty in crowdsourced annotation projects

Managing projects on MTurk

If you're considering running a crowdsourcing project on Mechanical Turk, please see *much* more detailed slides from last year's slide deck:

http://web.stanford.edu/class/cs224u/2014/slides/2013/cs224u-slides-02-05.pdf

And consult with Chris, who has experience in this!

Will crowdsourcing work?

- One hears that crowdsourcing is just for quick, simple tasks.
- This has not been our (Chris’) experience. We have had people complete long questionnaires involving hard judgments.
- To collect the Cards corpus, we used MTurk simply to recruit players to play a collaborative two-person game.
- If you post challenging tasks, you have to pay well.
- There are limitations, though:
    - If the task requires any training, it has to be quick and easy (e.g., learning what your labels are supposed to mean).
    - You can’t depend on technical knowledge.
    - If your task is highly ambiguous, you need to reassure workers and tolerate more noise than usual.

Appendix: evaluation metrics

Evaluation metrics for classification

- Contingency tables & confusion matrices
- Accuracy
- Precision & recall
- F-measure
- AUC (area under ROC curve)
- Sensitivity & specificity
- PPV & NPV (positive/negative predictive value)
- MCC (Matthews correlation coefficient)

Contingency tables

- In binary classification, each instance has actual label ("gold")
- The model assigns to each instance a predicted label ("guess")
- A pair of labels [actual, predicted] determines an outcome
  - E.g., [actual:false, predicted:true] → false positive (FP)
- The contingency table counts the outcomes
- Forms basis of many evaluation metrics: accuracy, P/R, MCC, ...

		guess	
		false	true
gold	false	TN true negative	FP false positive
	true	FN false negative	TP true positive

		guess	
		false	true
gold	false	51	9
	true	4	36

Confusion matrices

- Generalizes the contingency table to multiclass classification
- Correct predictions lie on the main diagonal
- Large off-diagonal counts reveal interesting “confusions”

		guess			
		Y	N	U	
gold	Y	67	4	31	102
	N	1	16	4	21
	U	7	7	46	60
		75	27	81	183

from MacCartney & Manning 2008

Accuracy

- Accuracy: percent correct among *all* instances
- The most basic and ubiquitous evaluation metric
- But, it has serious limitations (what?)

		guess		
		F	T	
gold	F	86	2	88
	T	9	3	12
		95	5	100

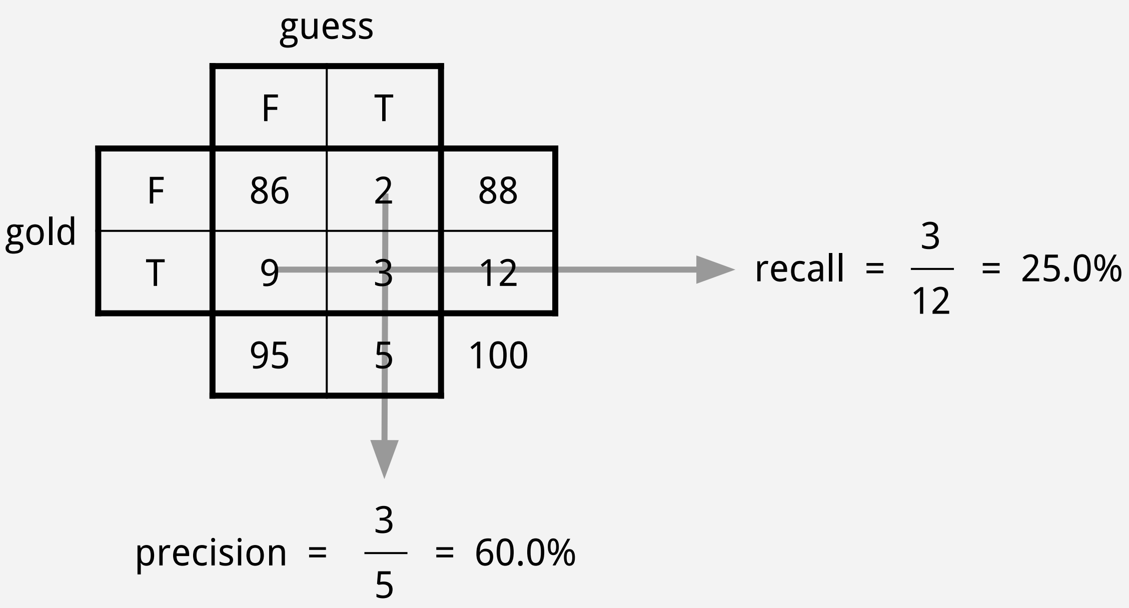
$$\text{accuracy} = \frac{86 + 3}{100} = 89.0\%$$

		guess			
		Y	N	U	
gold	Y	67	4	31	102
	N	1	16	4	21
	U	7	7	46	60
		75	27	81	183

$$\text{accuracy} = \frac{67 + 16 + 46}{183} = 70.5\%$$

Precision & recall

- Precision: % correct among items where guess=true
- Recall: % correct among items where gold=true
- Preferred to accuracy, especially for highly-skewed problems



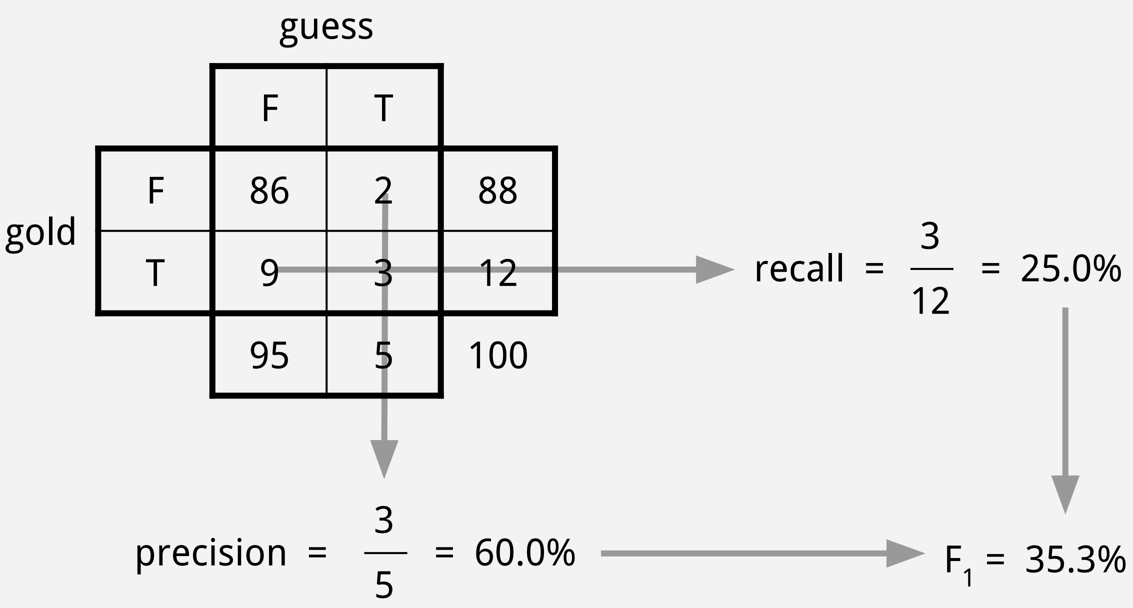
		guess		
		F	T	
gold	F	86	2	88
	T	9	3	12
		95	5	100

recall $= \frac{3}{12} = 25.0\%$

precision $= \frac{3}{5} = 60.0\%$

F_1

- It's helpful to have a single measure which combines P and R
- But we *don't* use the arithmetic mean of P and R (why not?)
- Rather, we use the harmonic mean: $F_1 = 2PR / (P + R)$



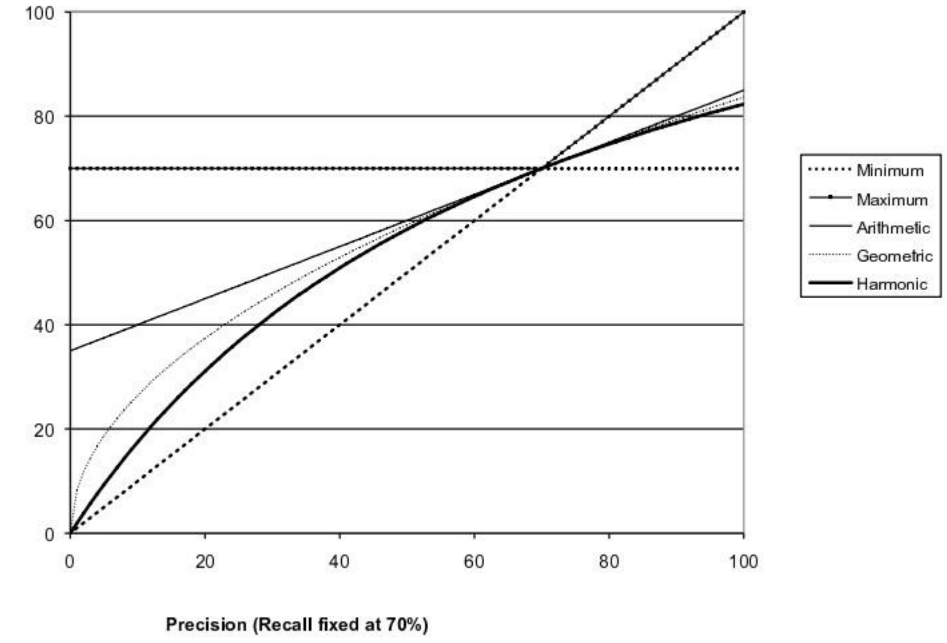
		guess		
		F	T	
gold	F	86	2	88
	T	9	3	12
		95	5	100

$$\text{recall} = \frac{3}{12} = 25.0\%$$

$$\text{precision} = \frac{3}{5} = 60.0\%$$

$$F_1 = 35.3\%$$

Why use harmonic mean?



► **Figure 8.1** Graph comparing the harmonic mean to other means. The graph shows a slice through the calculation of various means of precision and recall for the fixed recall value of 70%. The harmonic mean is always less than either the arithmetic or geometric mean, and often quite close to the minimum of the two numbers. When the precision is also 70%, all the measures coincide.

from Manning et al. 2009

F-measure

- Some applications need more precision; others, more recall
- F_β is the *weighted* harmonic mean of P and R
- $F_\beta = (1 + \beta^2)PR / (\beta^2 P + R)$

β = 2.0 (favor recall)

β = 1.0 (neutral)

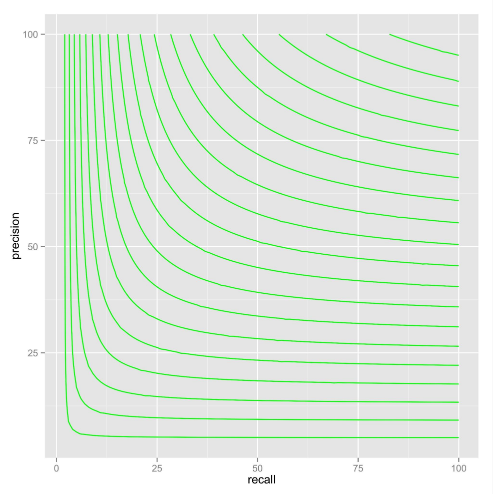
β = 0.5 (favor precision)

		recall			
		0.10	0.30	0.60	0.90
precision	0.10	0.10 0.10 0.10	0.21 0.15 0.12	0.30 0.17 0.12	0.35 0.18 0.12
	0.30	0.12 0.15 0.21	0.30 0.30 0.30	0.50 0.40 0.33	0.64 0.45 0.35
	0.60	0.12 0.17 0.30	0.33 0.40 0.50	0.60 0.60 0.60	0.82 0.72 0.64
	0.90	0.12 0.18 0.35	0.35 0.45 0.64	0.64 0.72 0.82	0.90 0.90 0.90

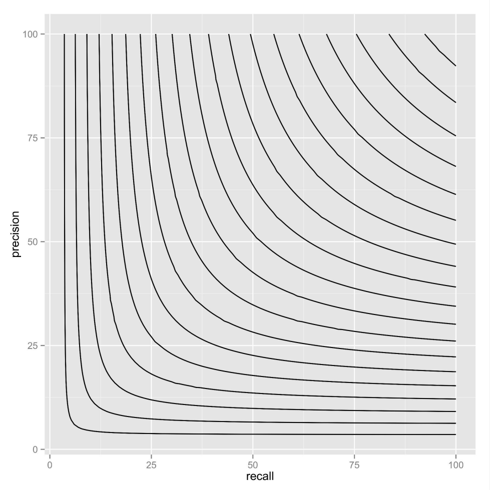
F-measure

- Some applications need more precision; others, more recall
- F_β is the *weighted* harmonic mean of P and R
- $F_\beta = (1 + \beta^2)PR / (\beta^2 P + R)$

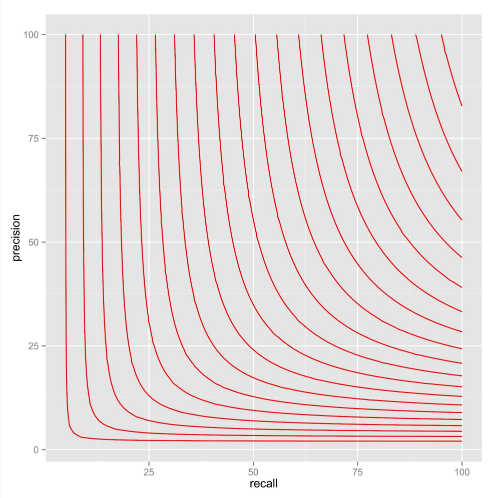
β = 0.5 (favor precision)



β = 1.0 (neutral)

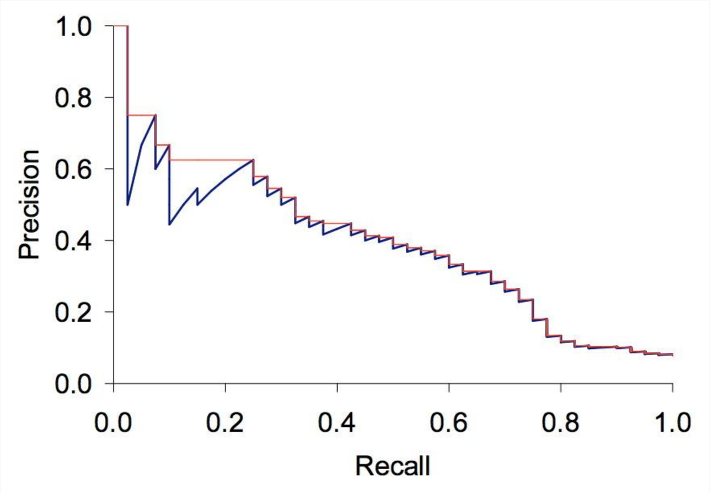


β = 2.0 (favor recall)



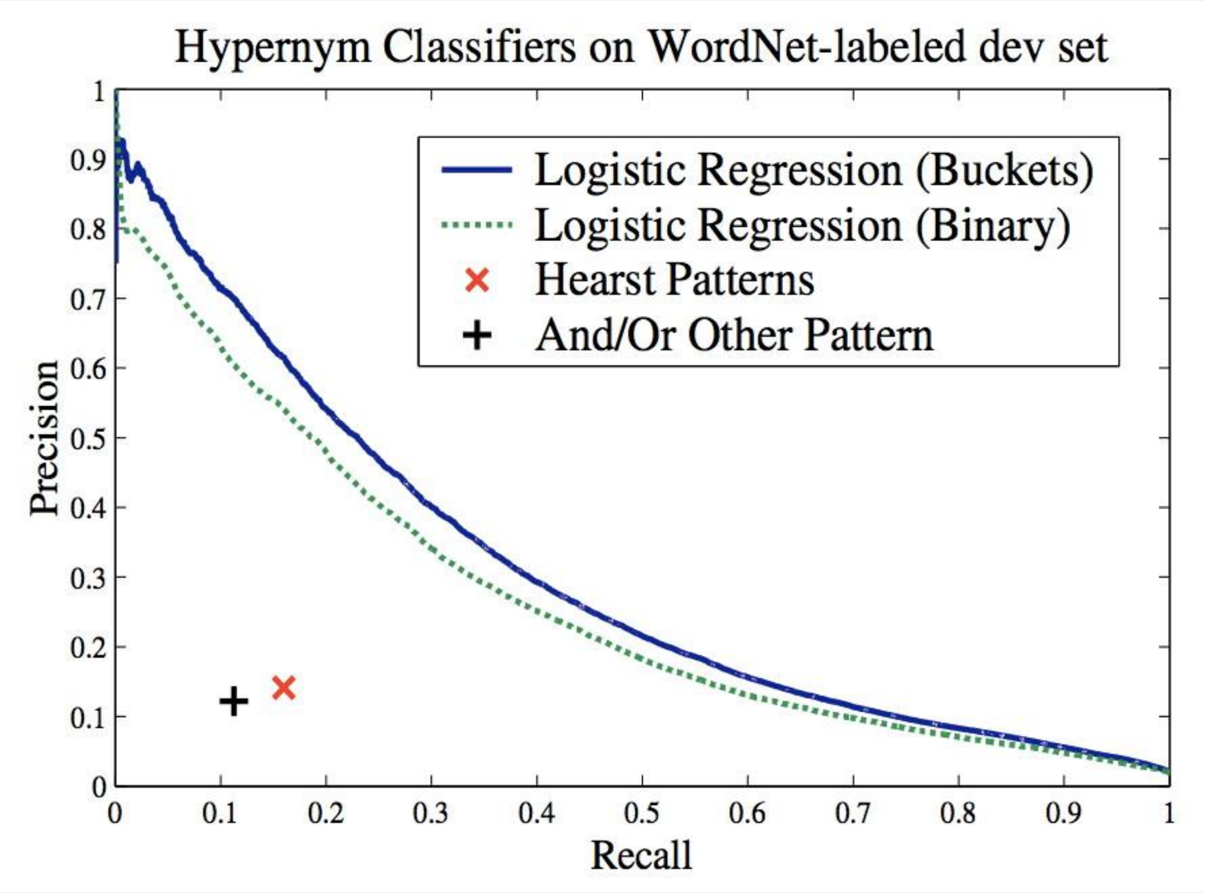
Precision vs. recall

- Typically, there's a trade-off between precision and recall
  - High threshold → high precision, low recall
  - Low threshold → low precision, high recall
- P/R curve facilitates making an explicit choice on trade-off
- Always put recall on x-axis, and expect noise on left (why?)



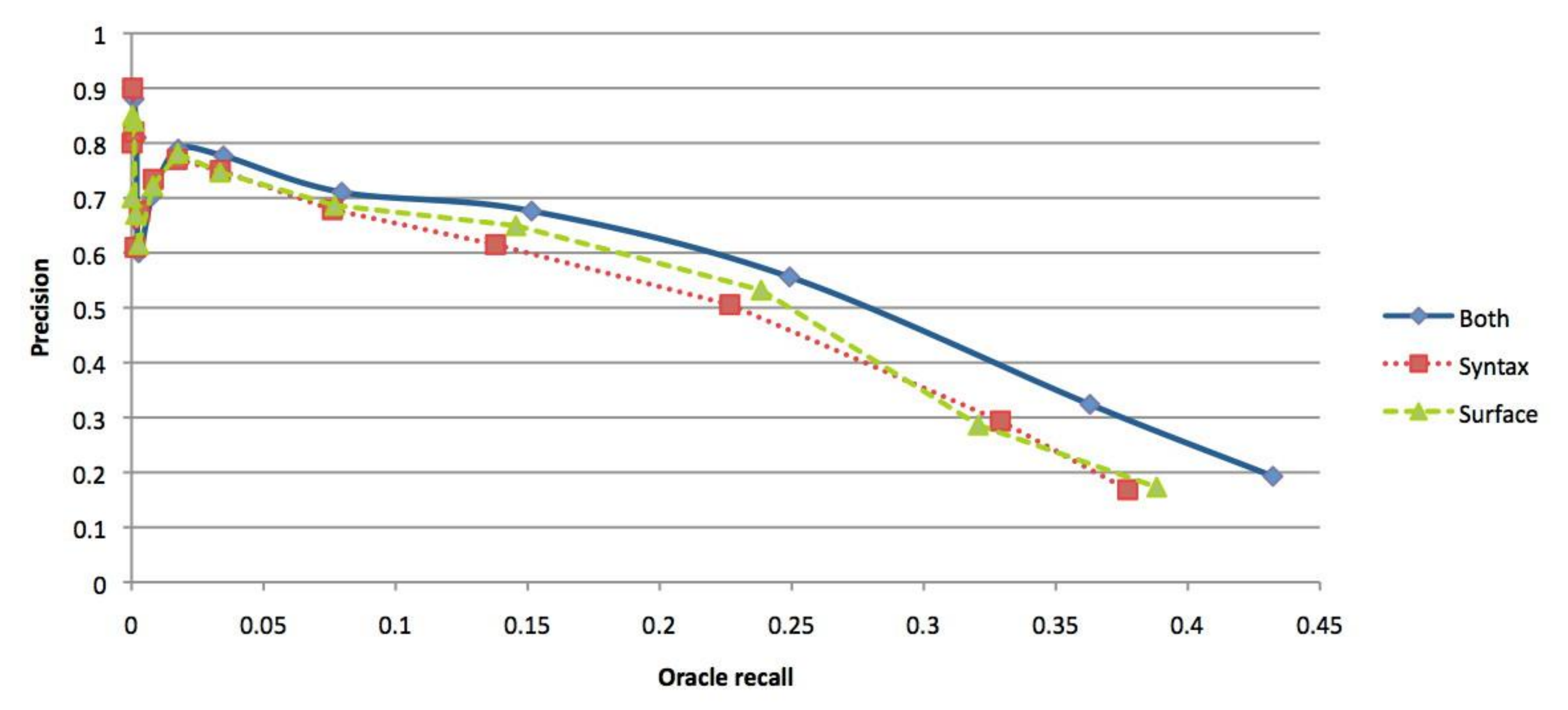
from Manning et al. 2009

Precision/recall curve example



from Snow et al. 2005

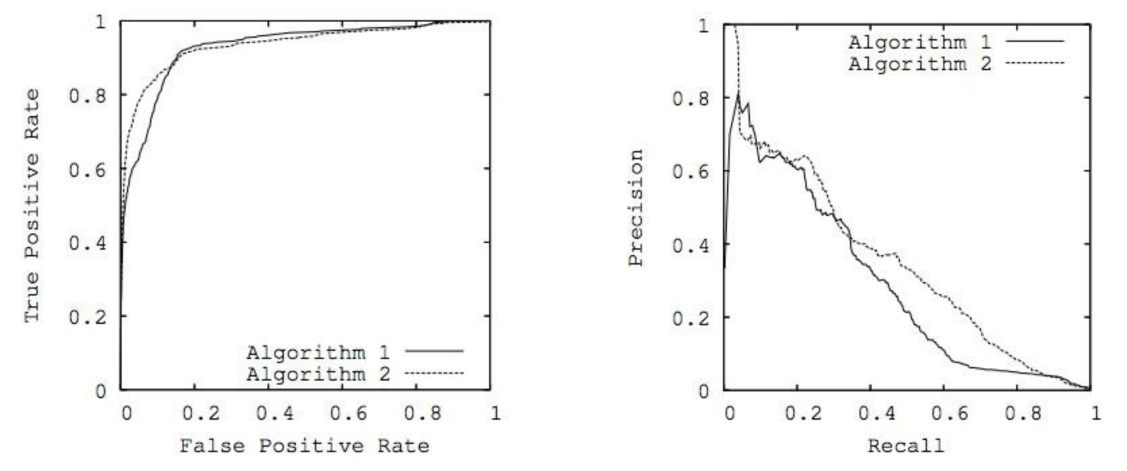
Precision/recall curve example



from Mintz et al. 2009

ROC curves and AUC

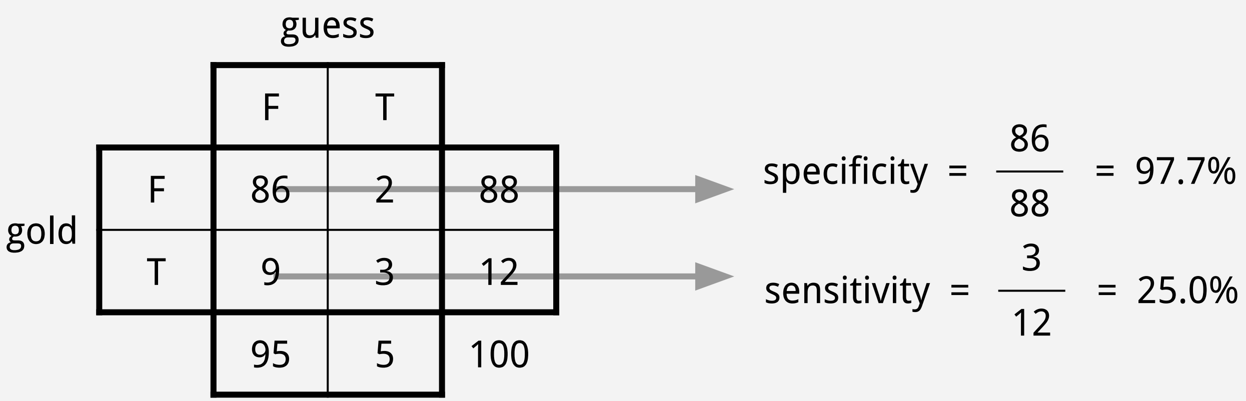
- ROC curve = receiver operating characteristic curve
  - An alternative to P/R curve used in other fields (esp. EE)
- AUC = area under (ROC) curve
  - Like F1, a single metric which promotes both P and R
  - But doesn't permit specifying tradeoff, and generally *unreliable*



from Davis & Goadrich 2006

Sensitivity & specificity

- Sensitivity & specificity look at % correct by actual label
  - Sensitivity: % correct among items where gold=true (= recall)
  - Specificity: % correct among items where gold=false
- An alternative to precision & recall
  - More common in statistics literature



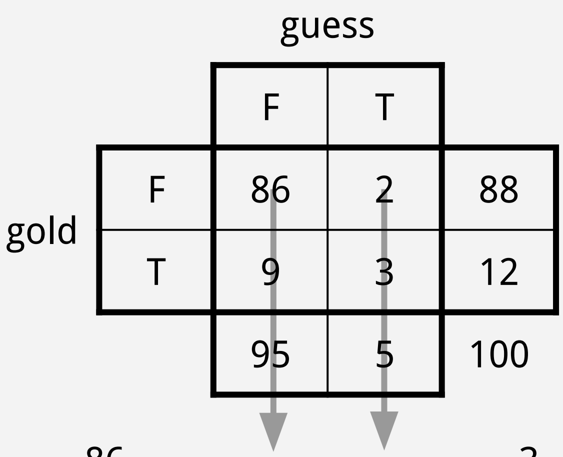
		guess		
		F	T	
gold	F	86	2	88
	T	9	3	12
		95	5	100

$$\text{specificity} = \frac{86}{88} = 97.7\%$$

$$\text{sensitivity} = \frac{3}{12} = 25.0\%$$

PPV & NPV

- PPV & NPV look at % correct by predicted label
  - PPV: % correct among items where guess=true (= precision)
  - NPV: % correct among items where guess=false
- An alternative to precision & recall
  - More common in statistics literature



		guess		
		F	T	
gold	F	86	2	88
	T	9	3	12
		95	5	100

$$\text{NPV} = \frac{86}{95} = 90.5\% \qquad \text{PPV} = \frac{3}{5} = 60.0\%$$

Matthews correlation coefficient (MCC)

- Correlation between actual & predicted classifications
- Random guessing yields 0; perfect prediction yields 1

$$\mathrm{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$$

		recall			
	MCC	0.05	0.35	0.65	0.95
precision	0.05	-0.90	—	—	—
	0.35	-0.11	-0.30	—	—
	0.65	0.08	0.22	0.30	0.36
	0.95	0.21	0.55	0.74	0.90

with prevalence = 0.50

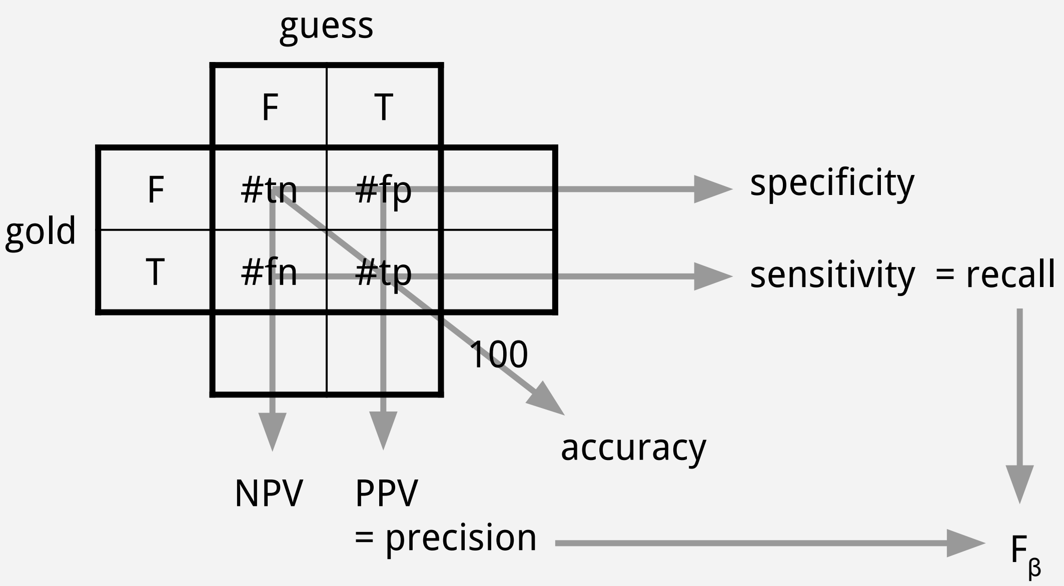
		recall			
	MCC	0.05	0.35	0.65	0.95
precision	0.05	-0.06	-0.15	—	—
	0.35	0.10	0.28	0.38	0.76
	0.65	0.17	0.45	0.61	0.74
	0.95	0.22	0.57	0.78	0.94

with prevalence = 0.10

Recap: metrics for classifiers

accuracy	proportion of all items predicted correctly
error	proportion of all items predicted incorrectly
sensitivity	accuracy over items actually true
specificity	accuracy over items actually false
PPV	accuracy over items predicted true
NPV	accuracy over items predicted false
precision	accuracy over items predicted true
recall	accuracy over items actually true
F1	harmonic mean of precision and recall
MCC	correlation between actual & predicted classifications

Recap: metrics for classifiers



guess

gold	F	T
F	#tn	#fp
T	#fn	#tp

100

specificity

sensitivity = recall

accuracy

NPV

PPV
= precision

F_β

Multiclass classification

- Precision, recall, F_1, MCC, ... are for binary classification
- For multiclass classification, compute these stats *per class*
  - For each class, project into binary classification problem
  - TRUE = this class; FALSE = all other classes
- Then average the results
  - Macro-averaging: equal weight for each class
  - Micro-averaging: equal weight for each instance
- See worked-out example on next slide

Multiclass classification

guess

		Y	N	U	
gold	Y	67	4	31	102
	N	1	16	4	21
	U	7	7	46	60
		75	27	81	183

class	precision		
Y	67/75	=	89.3%
N	16/27	=	59.3%
U	46/81	=	56.8%

Macro-averaged precision:

$$\frac{89.3 + 59.3 + 56.8}{3} = 68.5\%$$

Micro-averaged precision:

$$\frac{75 \cdot 89.3 + 27 \cdot 59.3 + 81 \cdot 56.8}{183} = 70.5\%$$

Evaluation metrics for retrieval

- Retrieval & recommendation problems
  - Very large space of possible outputs, many good answers
  - But outputs are simple (URLs, object ids), not structured
- Can be formulated as binary classification (of *relevance*)
- Problem: can’t identify all positive items in advance
  - So, can’t assess recall — look at *coverage* instead
  - Even precision is tricky, may require semi-manual process
- Evaluation metrics for ranked retrieval
  - Precision@k
  - Mean average precision (MAP)
  - Discounted cumulative gain

Evaluation metrics for complex outputs

- If outputs are numerous *and* complex, evaluation is trickier
  - Text (e.g., automatic summaries)
  - Tree structures (e.g., syntactic or semantic parses)
  - Grid structure (e.g., alignments)
- System outputs are unlikely to match gold standard exactly
- One option: manual eval — but slow, costly, subjective
- Another option: *approximate* comparison to gold standard
  - Give partial credit for partial matches
  - Text: n-gram overlap (ROUGE)
  - Tree structures: precision & recall over subtrees
  - Grid structures: precision & recall over pairs

Evaluation metrics for clustering

- Pairwise metrics (Hatzivassiloglou & McKeown 1993)
  - Reformulate as binary classification over *pairs* of items
  - Compute & report precision, recall, F1, MCC, ... as desired

- B^3 metrics (Bagga & Baldwin 1998)
  - Reformulate as a *set* of binary classification tasks, one per item
  - For each item, predict whether other items are in same cluster
  - Average per-item results over items (micro) or clusters (macro)

- Intrusion tasks
  - In predicted clusters, replace one item with random "intruder"
  - Measure human raters' ability to identify intruder

- See Homework 2, Yao et al. 2012

Other evaluation metrics

- Regression problems
  - When the output is a real number
  - Pearson's R
  - Mean squared error

- Ranking problems
  - When the output is a rank
  - Spearman's rho
  - Kendall's tau
  - Mean reciprocal rank