Domain Adaptation in Machine Translation

Marine Carpuat
National Research Council Canada

Marine.Carpuat@nrc.gc.ca

Old Domain (Parliament)	
Original	monsieur le président, les pêcheurs de homard de la région de l'atlantique sont dans une situation catastrophique.
Reference	mr. speaker, lobster fishers in atlantic canada are facing a disaster.
System	mr. speaker, the lobster fishers in atlantic canada are in a mess.
New Domain	
Original	comprimés pelliculés blancs pour voie orale.
Reference	white film-coated tablets for oral use.
System	white pelliculés tablets to oral.
New Domain	
Original	mode et voie(s) d'administration
Reference	method and route(s) of administration
System	fashion and voie(s) of directors

Domain adaptation in MT

- Translating across domains is hard, but often necessary
- Lots of interest in domain adaptation driven by
  - Increasing amounts of parallel training data
  - Increasing diversity of data sources

What is a domain?

- No clear definition of domain
  – Related to topic, genre, register

- Defined in practice by datasets/tasks
  - Single homogeneous domain

    e.g. Parliament proceedings
  - Large old domain & small new domain

    e.g. Parliament + News or Science
  - Large data collection from various sources

    e.g. NIST OpenMT, DARPA BOLT, WMT gigafren …

What is domain adaptation?

From **classical "single-domain" learning**…

- predict $x \to y$
- *training* and *test* data generated from the same *distribution* $(x, y) \sim \Pr[x, y]$

… to **Domain Adaptation**

- Port system trained on old (aka source) domain to new (aka target) domain

$(x, y) \sim \Pr_S[x, y] \qquad (x, y) \sim \Pr_T[x, y]$

No “one size fits all” approach

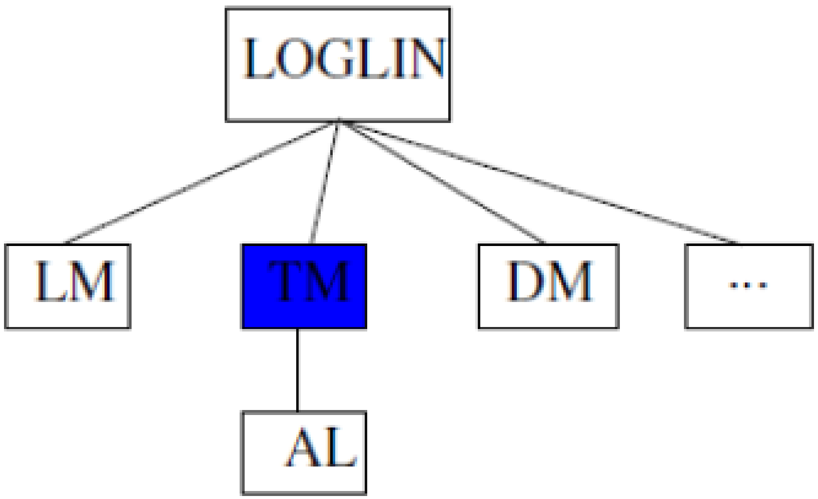
- Lots of domain adaptation work in Machine Learning
  - see [Blitzer & Daumé III, ICML 2010] for an overview
- But not directly applicable to MT
  - heterogeneous components trained independently
  - large variety of settings

Addressing domain shift in MT

- General approach
  – adjust MT parameters to optimize performance for a test set, based on some knowledge of its domain

- Various settings
  – amount of in-domain training data: small, dev-sized, none (just source text)
  – nature of out-of-domain data: size, diversity, labeling
  – monolingual resources: source and target, in-domain or not, comparable or not
  – latency: offline, tuning, dynamic, online, (interactive)

What to adapt?



- Language model (LM)
  - Effective and simple
  - Previous work from speech
  - Perplexity-based interpolation popular
- Translation model (TM)
  - Most popular target
  - Gains can be elusive
- Distortion/Reordering model (DM)
- Log-linear model
  - limited scope if in-domain dev set available

How to adapt to a new domain?

- Filter training data
  - Select from out-of-domain data based on similarity to test domain
- Corpus weighting
  - At sub-corpora, sentence or phrase-pair level
- Model combination
  - Train submodels on different subcorpora
- Self training
  - Use MT to generate new parallel data
- Latent semantics
  - Exploit latent topic structure
- Mining comparable corpora

Domain adaptation in MT

- Lots of recent work, but still many open questions
- I'll focus on 2 of them today
  - What goes wrong when porting a MT system to a new domain?
  - What does "domain adaptation" mean in more heterogeneous data settings?

I. WHAT GOES WRONG WHEN PORTING MT TO A NEW DOMAIN?

When porting a machine translation system to a new domain…

1. what goes wrong?

analysis of lexical choice errors

[Irvine, Morgan, Carpuat, Daumé III, Munteanu, TACL 2013]

2. how can we fix common errors?

new task to address under-studied "sense" errors

[Carpuat, Daumé III, Henry, Irvine, Jagarlamudi, Rudinger,. ACL 2013]

S^4 Taxonomy of Adaptation Errors

New Domain (Medical)	
Original	mode et voie(s) d‘ administration
Reference	method and route(s) of administration
System	**fashion** and **voie(s)** of **directors**

Seen: Never seen this word before "voie(s)"

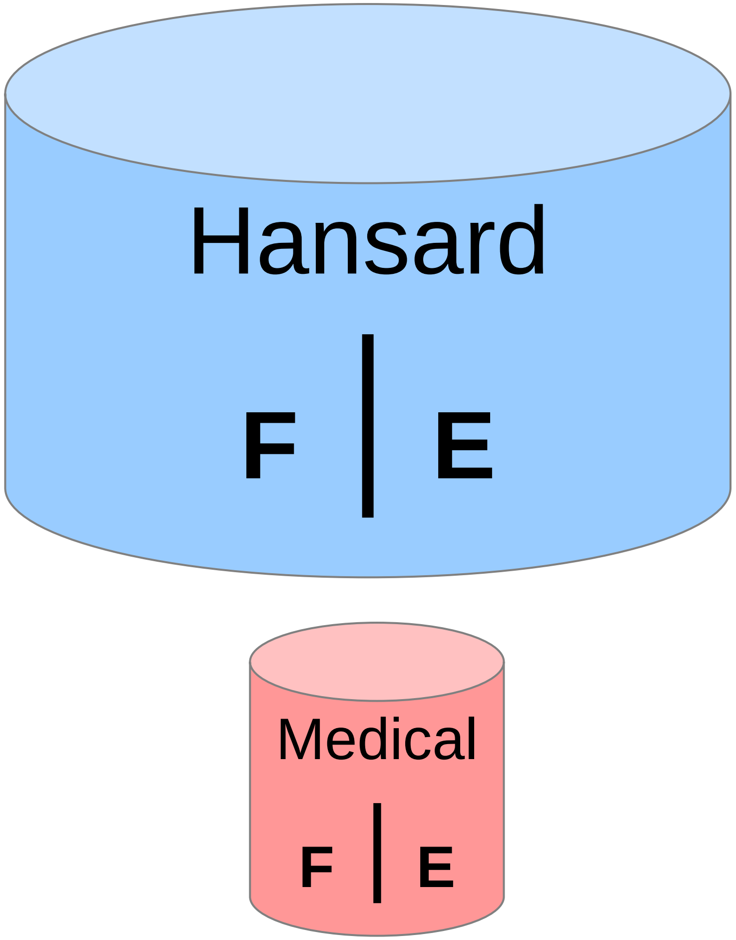
Sense Never seen this word used in this way
"mode" → "method"

Score Wrong output is scored higher
"administration" → "administration"
or "directors"?

Search Decoding/Search erred

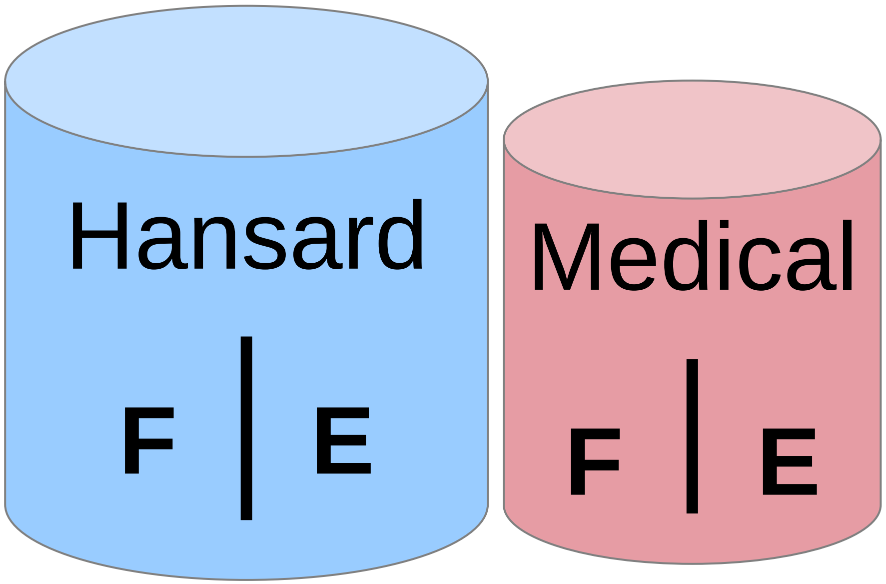
Measuring impact of S4 errors

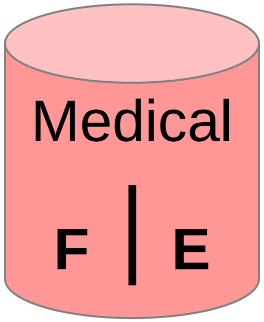
- We port MT system to new domain
  - Assumption: no new domain training data
  - **Old domain** resources
    - Large parallel training set
  - New domain resources
    - Tuning + test set



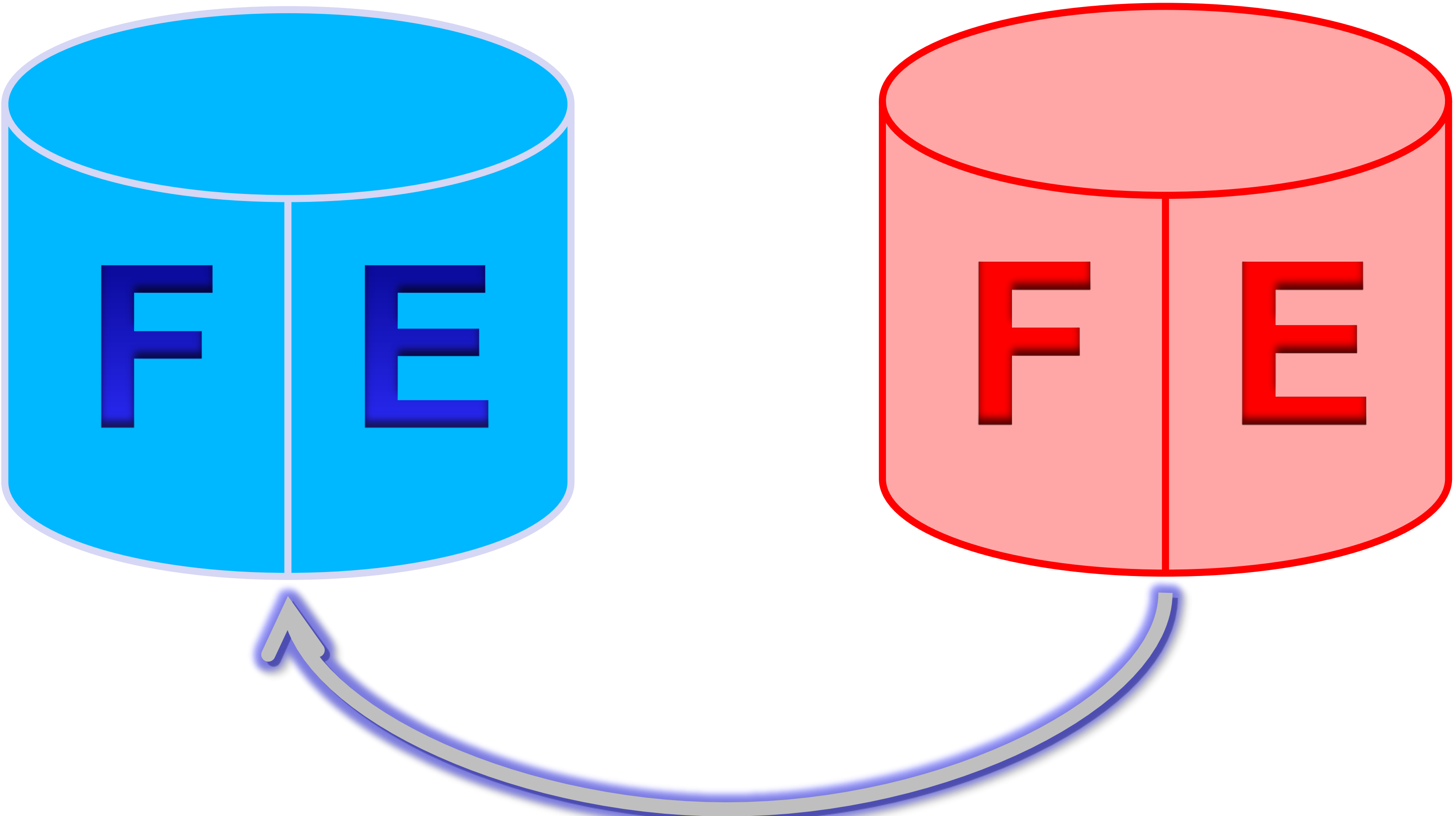
Measuring impact of S4 errors

- Compare translation quality with “oracle”
  - Trained on
    - large old domain corpus
    - large new domain corpus
  - new domain tuning set



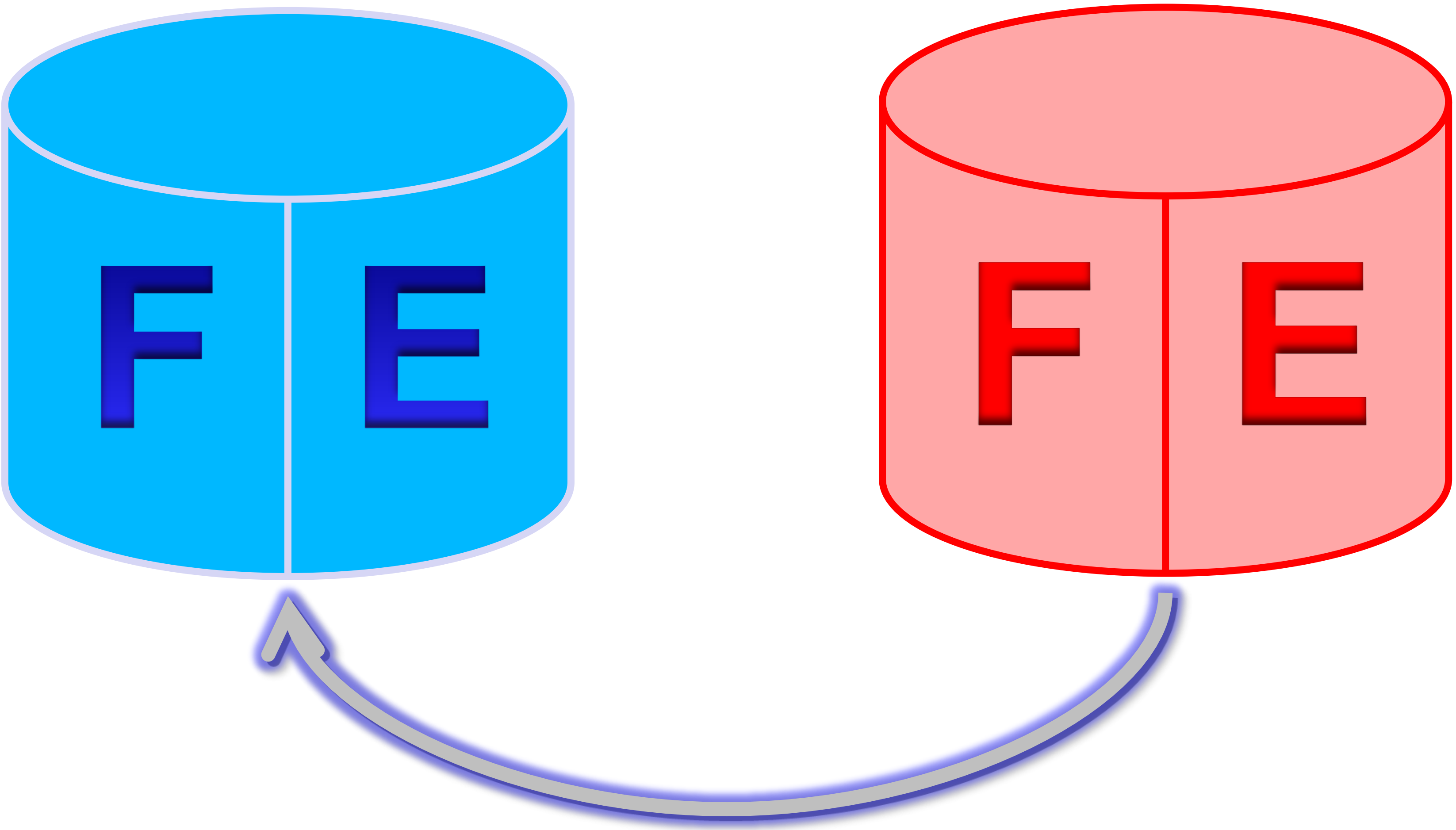


Measuring SEEN effects



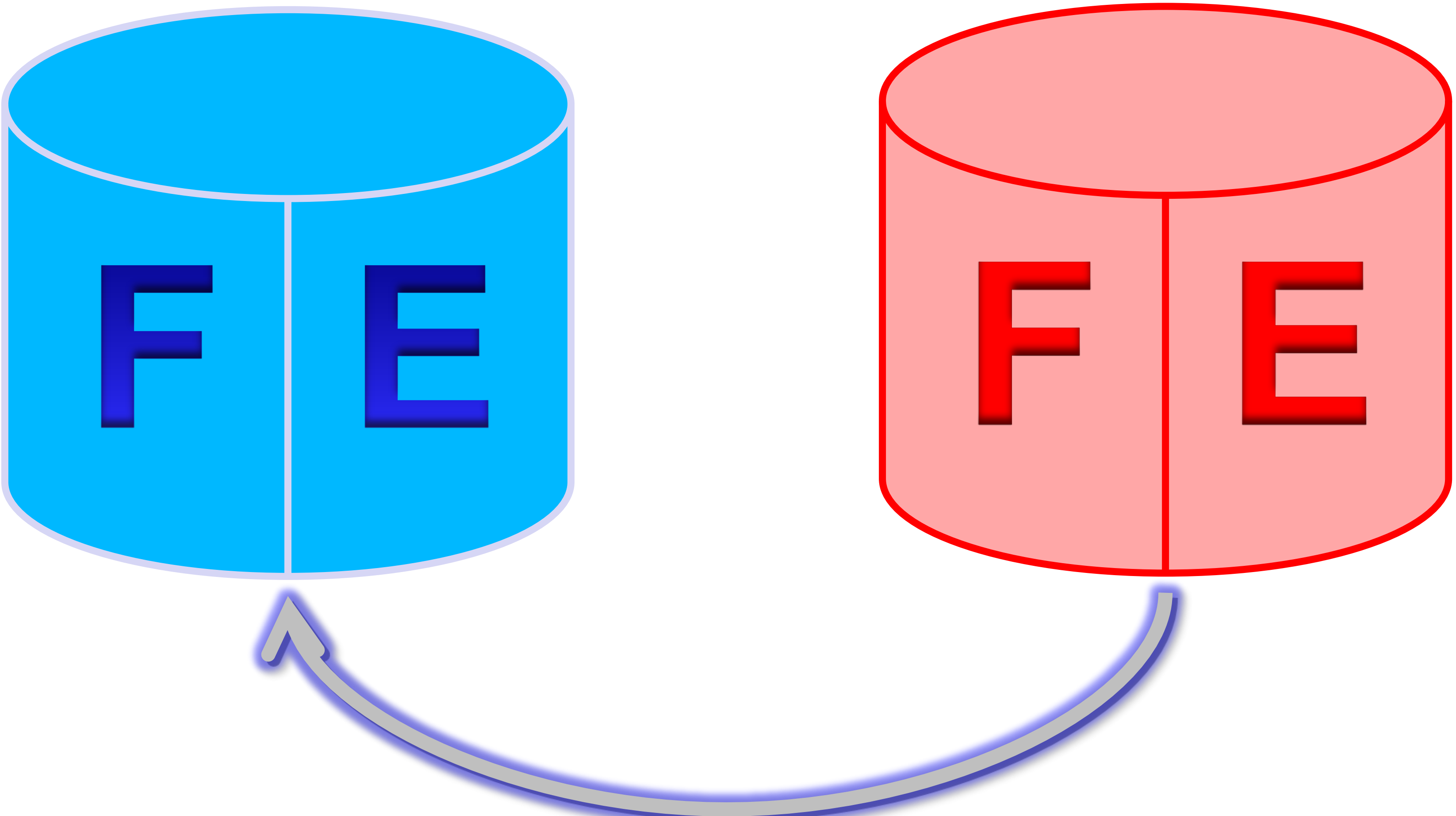
Add all phrase pairs with
previously unseen F side

Measuring SENSE effects



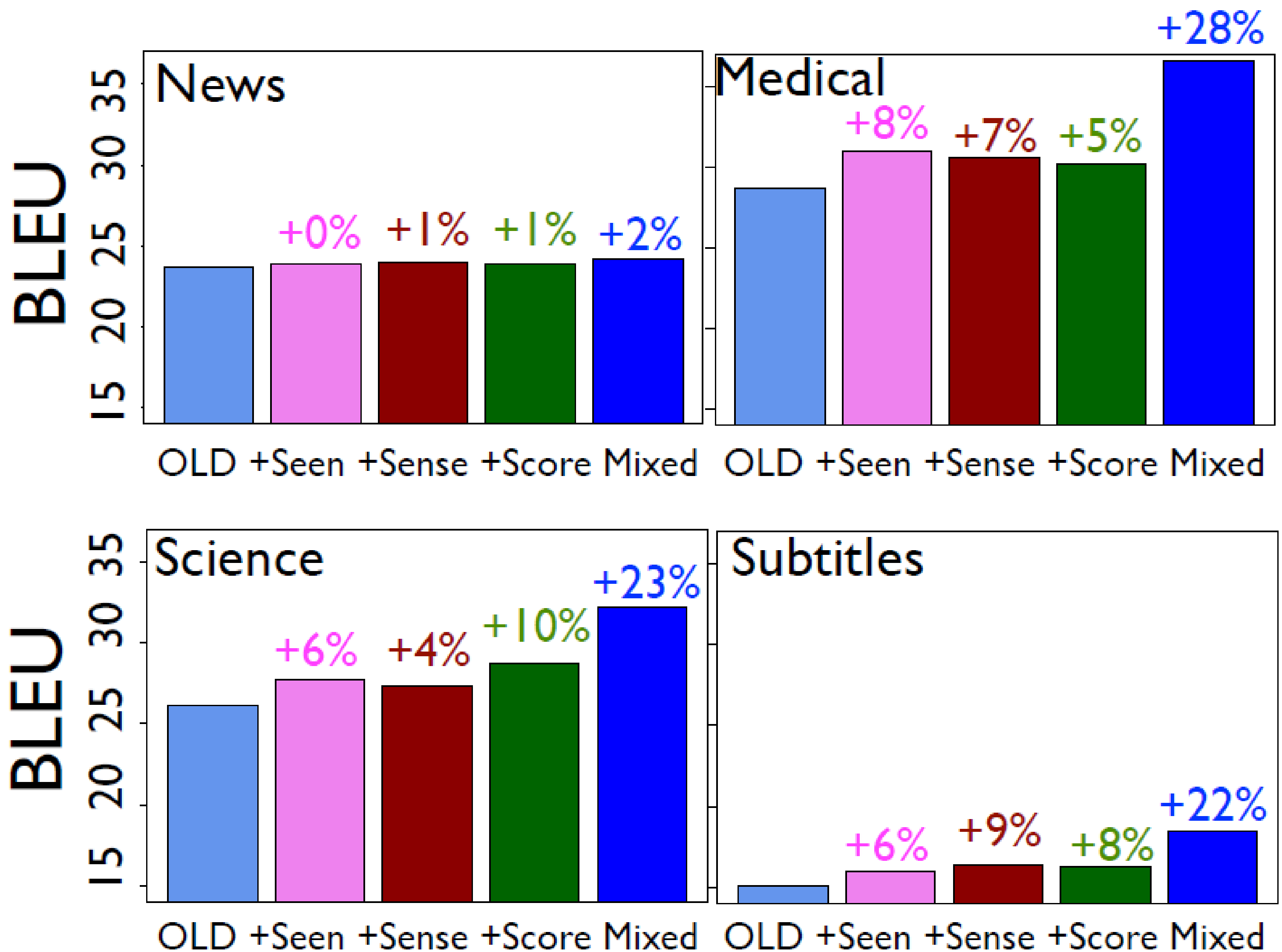
Add all phrase pairs with
previously seen F side, but unseen translation

Measuring SCORE effects



Add all phrase pairs, period
(and keep new domain scores)

Impact of fixing S^4 errors on BLEU



How to fix the S^4 errors (without new domain parallel data)

Seen: Dictionary mining for unseen terms

[Fung & Yee 1998, Haghighi et al. 2008, Daumé III & Jagarlamudi 2011, inter alia]

Score: Existing domain adaptation techniques

[Blitzer et al. 2006, Bickel et al. 2007, inter alia]

Sense: SenseSpotting + {dictionary mining, active learning}

[Bloodgood & CCB 2010]

SenseSpotting

- **Why?** MT performance across domains degrades due to lexical choice errors
- **What?** New task to identify word occurrences (tokens) that gain a new sense in new domains
- **How?** Automatic annotation from parallel text + supervised learning

SenseSpotting task definition

Old domain translation lexicon

rapport ||| report ||| 0.8
rapport ||| connection ||| 0.1
rapport ||| study ||| 0.05
rapport ||| relationship ||| 0.05

New domain sentences

- ces données sont basées sur le **rapport** d’ étude clinique

  this data is based on clinical study **report** **(-)**

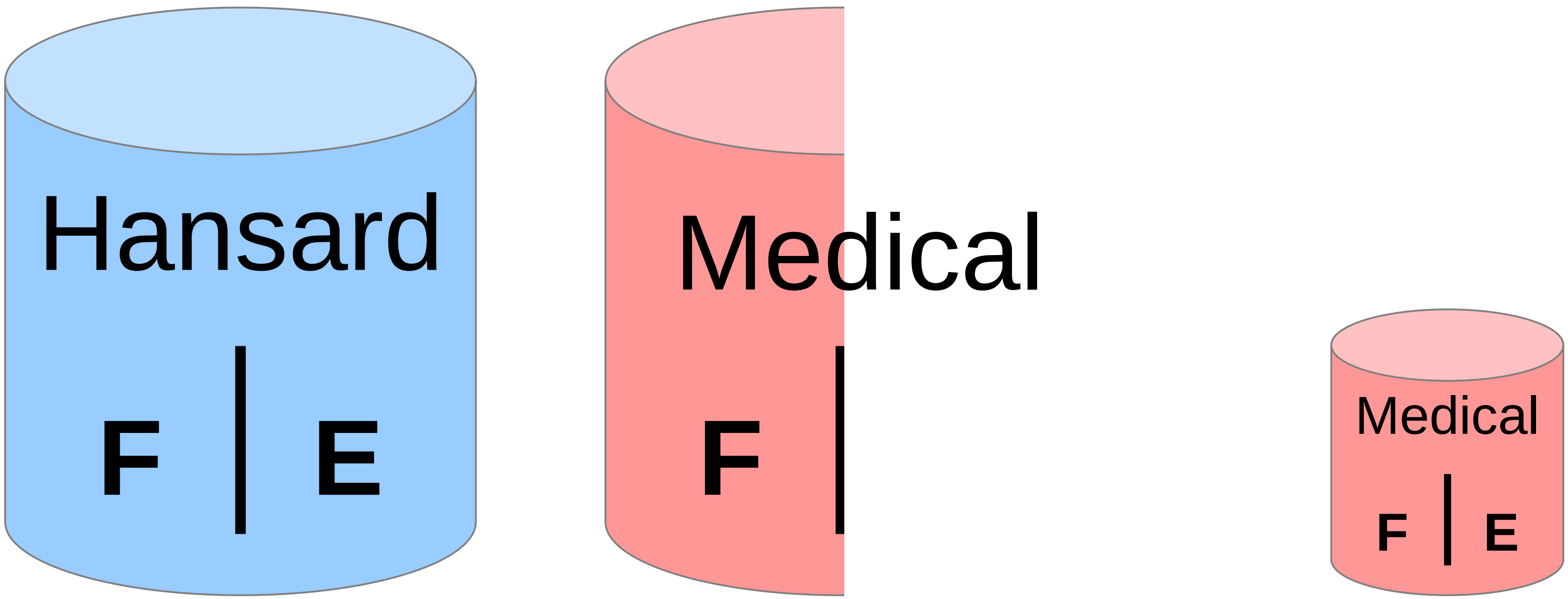
- le **rapport** cholestérol total / hdlc est resté stable

  the **ratio** **(+)** of total cholesterol : hdlc was unchanged

Key aspects of SenseSpotting

- Sense inventory is defined by the MT lexicon [Chan et al. 2007, Carpuat & Wu, 2007, inter alia]
- New Senses are detected at the token-level

Data requirements



Extract candidate terms and statistics

Extract useful statistics

Train model parameters

Classification set-up

Logistic regression model trained with VW

- L1 or L2 regularized based on tuning data

16-fold cross validation at the type level

- Never test on type seen in training!
- E.g., train on “mode”, “administration”; test on “rapport”

Evaluation metric: AUC

- area under the ROC curve
- Pr(a true positive outranks a true negative)

Indicators of new sense

New senses alter corpus-level word frequency

New senses alter document-level context

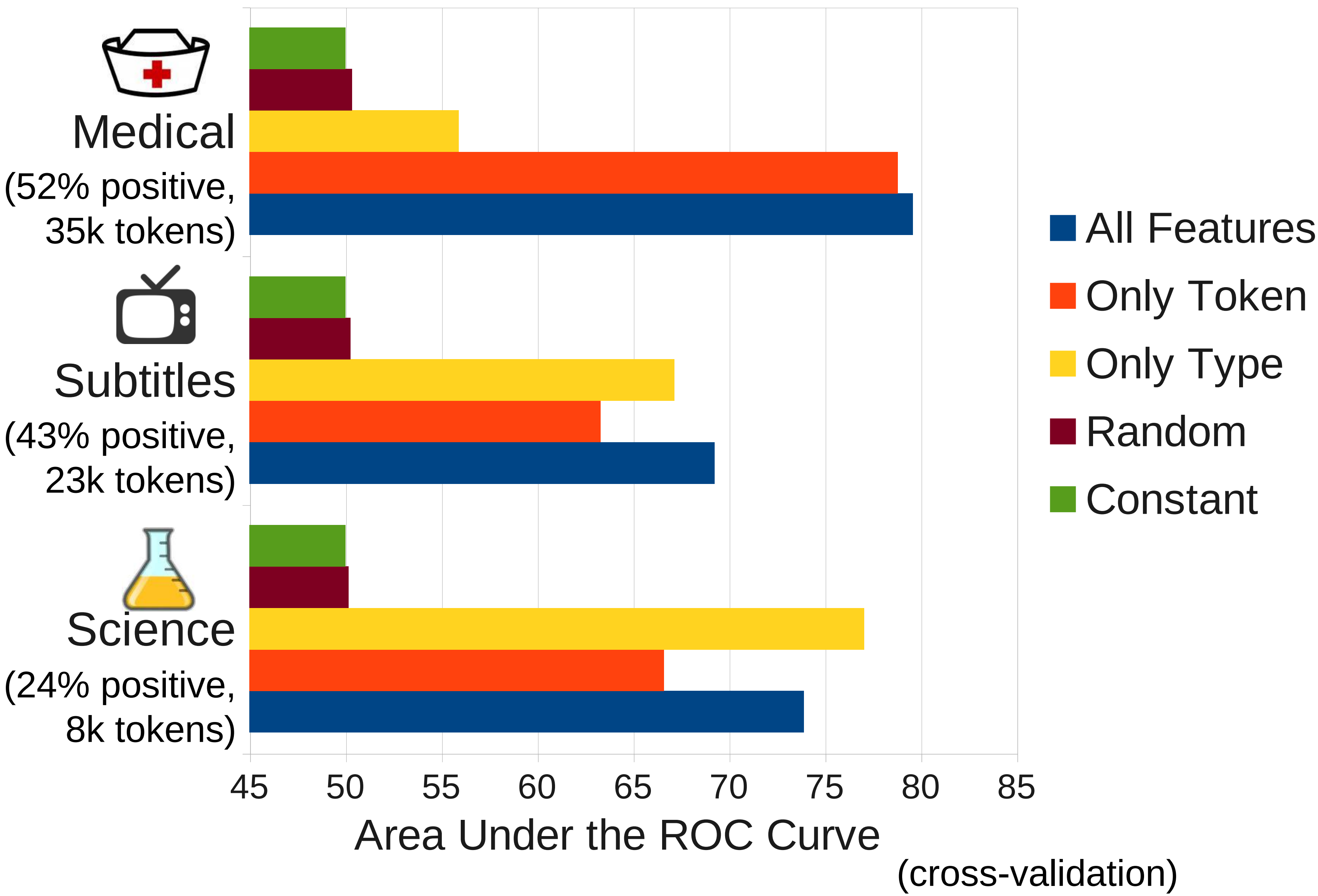
- topic distribution

New senses alter local context

- n-gram language model
- distributional similarity
- context-dependent translation model

Computed at both type and token levels

SenseSpotting results



Part I: Summary

We used **automatic annotation** derived from parallel corpora to address key questions

- what goes wrong when translating across domains?
  - All errors categories (seen,sense,score) matter
- how can we fix common errors?
  - proposed new task to address under-studied “sense” errors

II. WHAT DOES "DOMAIN ADAPTATION" MEAN IN MORE HETEROGENEOUS DATA SETTINGS?

How to estimate MT models from heterogeneous data?

- So far we have studied clear cut domain adaptation tasks (Europarl -> Medical)
- But we often train on more heterogeneous data

- How to robustly estimate models
  - from heterogeneous data
  - to achieve good translation quality on various test domains?

[Carpuat, Goutte and Foster, WMT 2014]

Estimating MT Models From Heterogeneous Data

Approaches

- Data selection
  [Moore & Lewis 2010, Axelrod et al. 2011…]
- Data weighting based on provenance
  [Chiang et al. 2011, Eidelman et al. 2012,…]
- Linear mixture models
  [Foster & Kuhn 2007, Foster et al. 2010, Sennrich 2012, …]
- Finer grained instance weighting
  [Foster et al. 2010, Hasler et al. 2014…]

  …

Defining Linear Mixtures With Heterogeneous Data

- We focus on translation probabilities
- Given K subsets of the training corpus

$$P(t|s) = \sum_{k=1}^{K} \lambda_k P_k(t|s)$$

  - How to define mixture components?
  - How to learn mixture weights?

Mixture Models for Robust MT

- We empirically study impact on BLEU of
  - Component definitions
  - Mixture weights

- Key findings
  - All mixture models improve BLEU
  - Surprisingly, domain knowledge is not necessary

How to set mixing weights?

$$P(t|s) = \sum_{k=1}^{K} \lambda_k P_k(t|s)$$

2 methods:

- Maximum likelihood weights
  - Requires dev data representative of test domain
  - Estimate joint distribution $\tilde{p}(s,t)$ from dev
  - Optimize ML objective using EM

$$\hat{\lambda} = \operatorname{argmax}_{\lambda} \sum_{s,t} \tilde{p}(s,t) \log \sum_{k=1}^{K} \lambda_k p_k(s|t)$$

How to set mixing weights?

$$P(t|s) = \sum_{k=1}^{K} \lambda_k P_k(t|s)$$

2 methods:

- Maximum likelihood weights
  - Requires dev data representative of test domain
- Uniform weights
  - Domain agnostic

How to define mixture components?

$$P(t|s) = \sum_{k=1}^{K} \lambda_k \textcolor{red}{P_k(t|s)}$$

We partition training data

- By hand, using domain knowledge
- By automatic clustering, to learn data-driven domain distinctions
- Randomly
  - Random partition
  - Random sample (with replacement)

Domain knowledge in linear mixture models

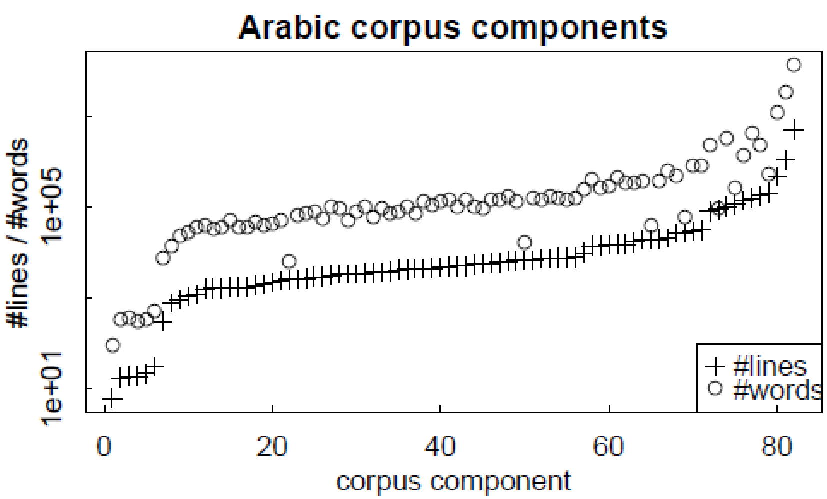
Corpus Components	Max Likelihood Weights	Uniform Weights
Manual partition	Dev + Train	Train
Automatic partition	Dev	None
Random partition	Dev	None
Random sample	Dev	None

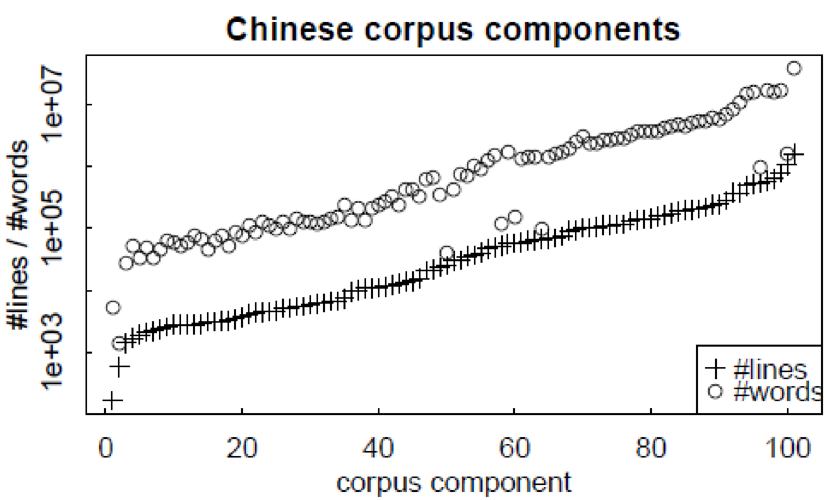
Experiments:
2 lang. pairs & 2 test domains

Arabic-English Training Conditions			
	segs	src	en
train	8.5M	262M	207M
Test Domain 1: Webforum			
	segs	src	en
dev (tune)	4.1k	66k	72k
web1 (eval)	2.2k	35k	38k
web2 (eval)	2.4k	37k	40k
Test Domain 2: News			
	segs	src	en
dev (tune)	1664	54k	51k
news (eval)	813	32k	29k

Chinese-English Training Conditions			
	segs	src	en
train	11M	234M	253M
Test Domain 1: Webforum			
	segs	src	en
dev (tune)	2.7k	61k	77k
web1 (eval)	1.4k	31k	38k
web2 (eval)	1.2k	29k	36k
Test Domain 2: News			
	segs	src	en
dev (tune)	1.7k	39k	24k
news (eval)	0.7k	19k	19k

Experiments: defining mixture components





- Split training set into homogeneous components
  - Same provenance, epoch, dialect, genre
- Arabic
  - 47 files, 15 genres, 4 dialects

  $\Rightarrow$ 82 basic components

  $\Rightarrow$ grouped into K = 10 components
- Chinese

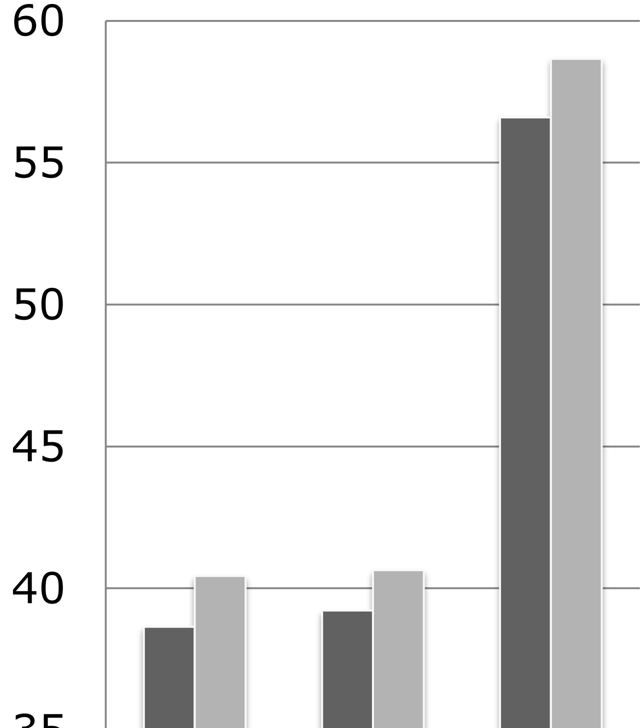
  $\Rightarrow$ 101 basic components

  $\Rightarrow$ grouped into K = 17

Experiments: Phrase-based MT system

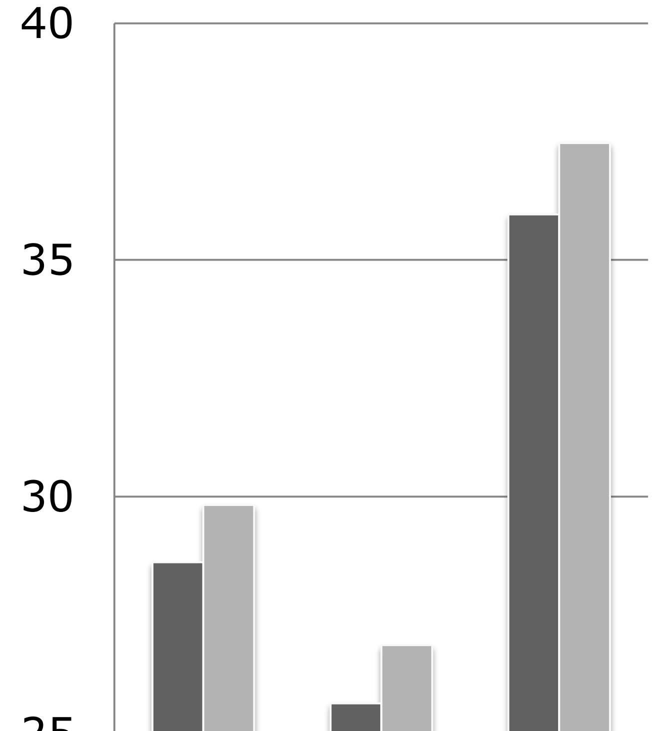
- Features
  - 4 phrase-table scores
    - Kneser-Ney smoothed translation probabilities x 2 [Chen et al. 2011]
    - Lexical weights x 2 [Zens & Ney 2004]
    - Counts summed across several word alignments (IBM2, HMM, IBM4)
  - hierarchical reordering, word penalty, distortion penalty
    [Galley & Manning 2008, Cherry 2013]
  - 3 5-gram language models
    - All training set, Gigaword, webforum or news only
  - Sparse features [Hopkins & May, 2011]
- Loglinear weights learned with batch lattice MIRA

Findings: linear mixtures significantly improve BLEU



	web1	web2	news
no mix	38.64	39.21	56.59
best mix	40.43	40.63	58.65

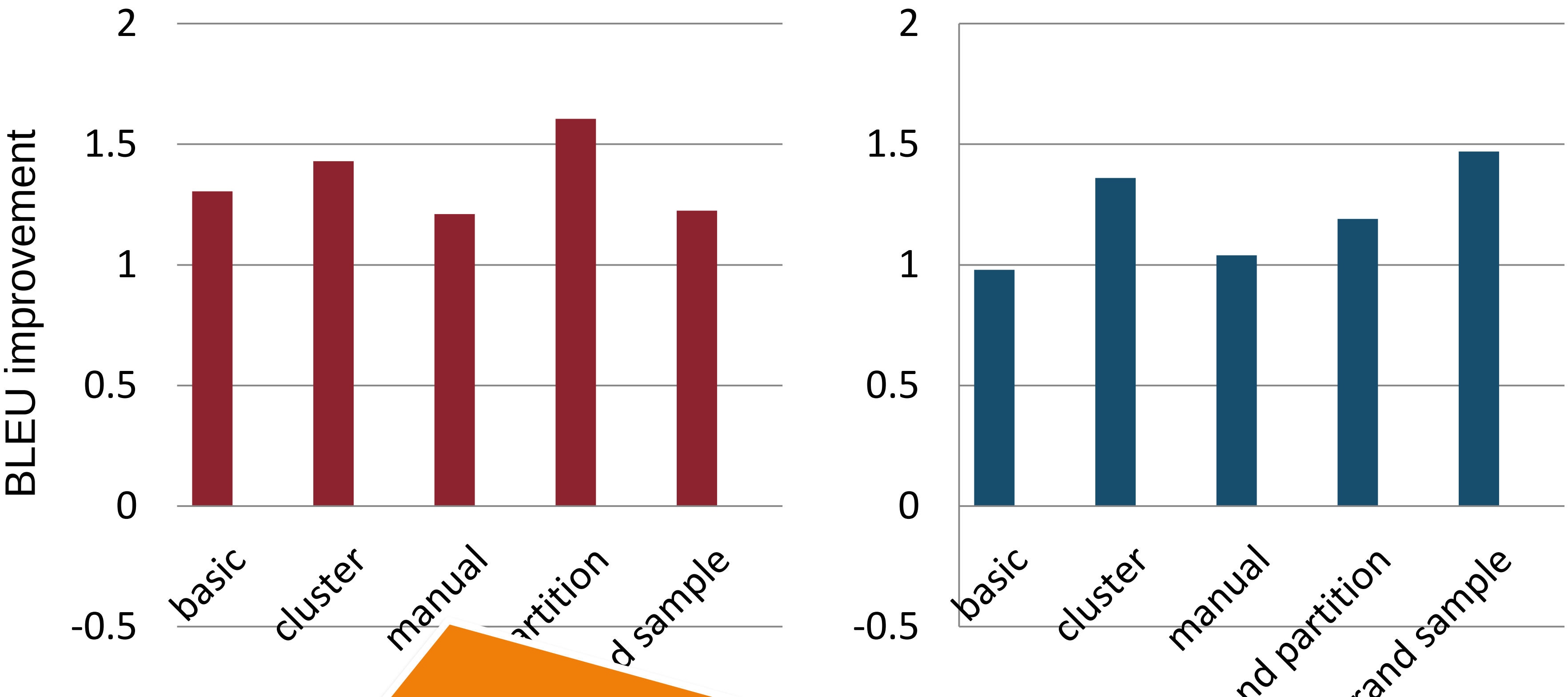
Arabic-English



	web1	web2	news
no mix	28.61	25.63	35.96
best mix	29.82	26.86	37.47

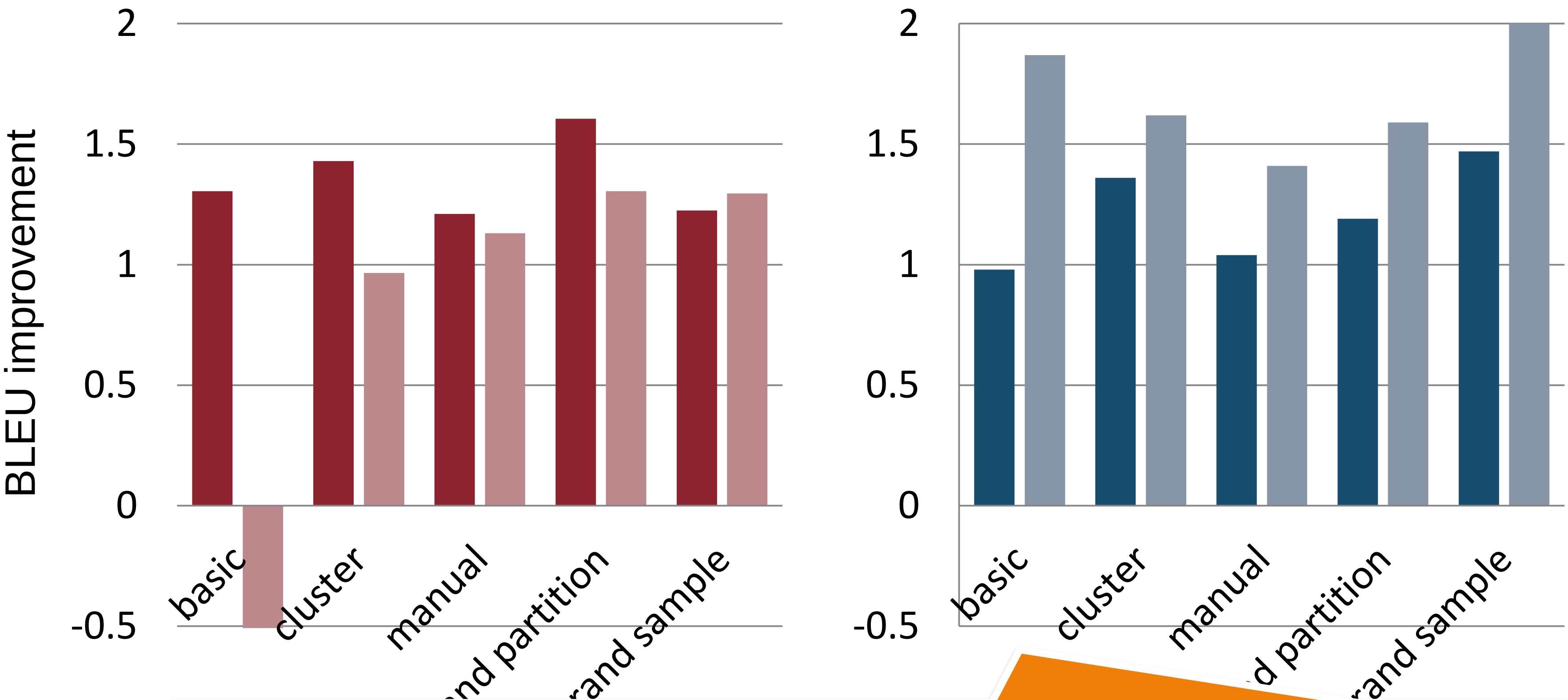
Chinese-English

ar-en: all mixture components improve BLEU



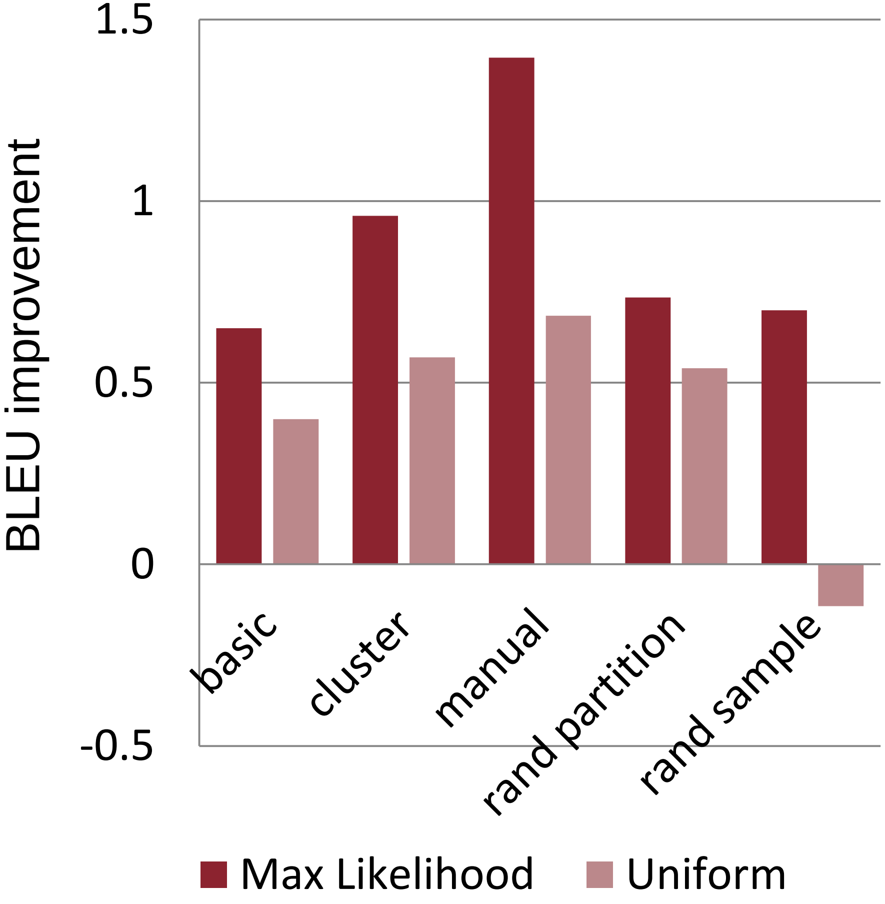
Explicitly modeling domain in mixture components does not help !

ar-en: mixing weights only have a small impact on BLEU

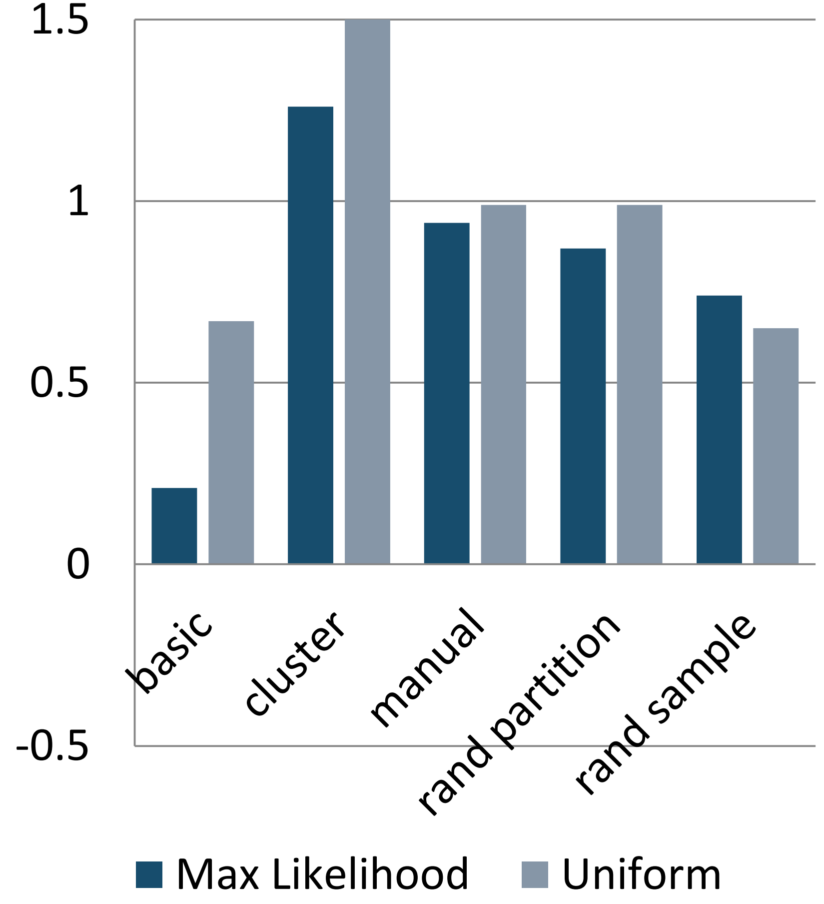


domain knowledge in mixing weights does not clearly help

zh-en: no consistent advantage from domain knowledge



Web domain



News domain

Why doesn't domain knowledge help more?

- Hypothesis: mixture models
  - don't capture domain specific translations
  - smooth translation distributions toward "general language" instead
  - learn more robust translation probabilities
    - Random sampling + averaging = bagging

      [Breiman 94]

Part II: Domain Adaptation in heterogeneous data settings

When learning mixture models from heterogeneous data

- should mixture components represent domains?
- should weights reflect proximity between components and test domain?

Part II: Domain Adaptation in heterogeneous data settings

Findings

- All mixtures improve BLEU
- Domain knowledge is not necessary
- Are mixture models just a form of smoothing toward “general language”?

Conclusion

- There's no data like more relevant data
  - Handling data heterogeneity matters
- Lots of "domain adaptation" results in the literature, but no clear picture yet
  - various data settings, targets for adaptation, approaches
- Key open questions remain
  - How exactly does translation quality degrade in new domains?
  - What domain knowledge do domain adaptation techniques actually capture?
  - …

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