PA153

Vít Baisa

MACHINE TRANSLATION

We consider only technical / specialized texts:

- web pages,
- technical manuals,
- scientific documents and papers,
- leaflets and catalogues,
- law texts and
- in general, texts from specific domains.

Nuances on different language levels in art literature are out of scope of current MT systems.

MACHINE TRANSLATION: ISSUES

In fact an output of MT is always revised. We distinguish pre-editing and post-editing.

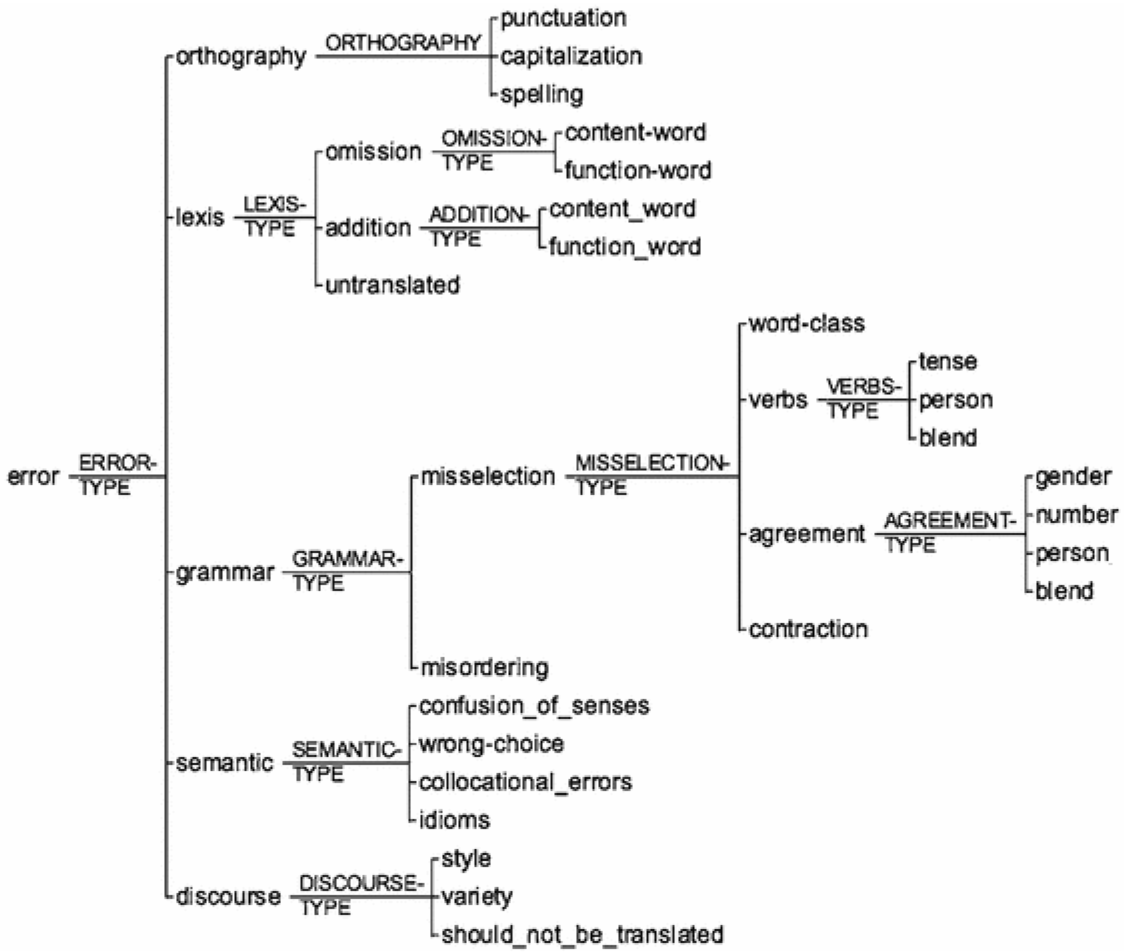
MT systems make different types of errors.

These mistakes are characteristic for human translators:

- wrong prepositions: (*I am in school*)
- missing determiners (*I saw man*)
- wrong tense (*Viděl jsem*: *I was seeing*), ...

For computers, errors in meaning are characteristic:

- *Kiss me honey. → Polib mi med.*



Costa, Ângela, et al. "A linguistically motivated taxonomy for Machine Translation error analysis." Machine Translation 29.2 (2015): 127-161.

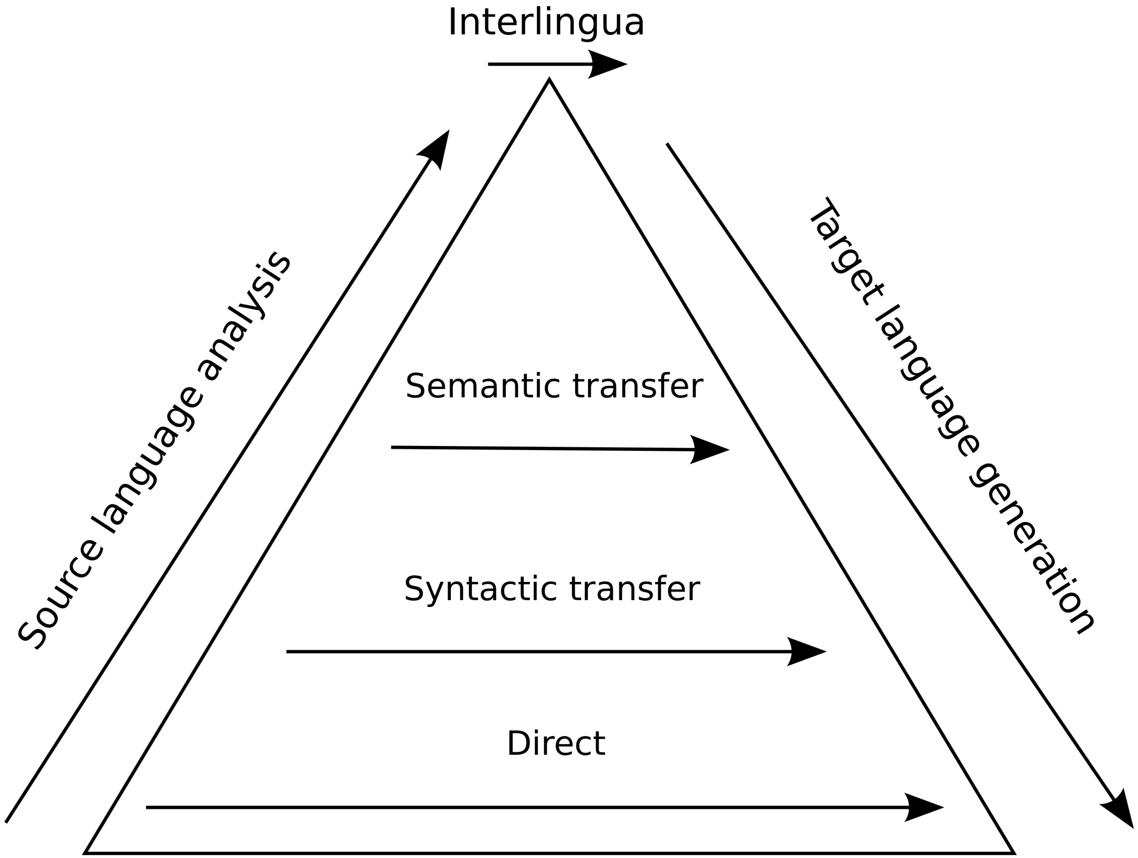
DIRECT METHODS FOR IMPROVING MT QUALITY

- limit input to a:
  - sublanguage (indicative sentences)
  - domain (informatics)
  - document type (patents)
- text pre-processing (e.g. manual syntactic analysis)

CLASSIFICATION BASED ON APPROACH

- rule-based, knowledge-based (RBMT, KBMT)
  - transfer
  - with interlingua
- statistical machine translation (SMT)
- hybrid machine translation (HMT, HyTran)
- neural networks

VAUQUOIS'S TRIANGLE



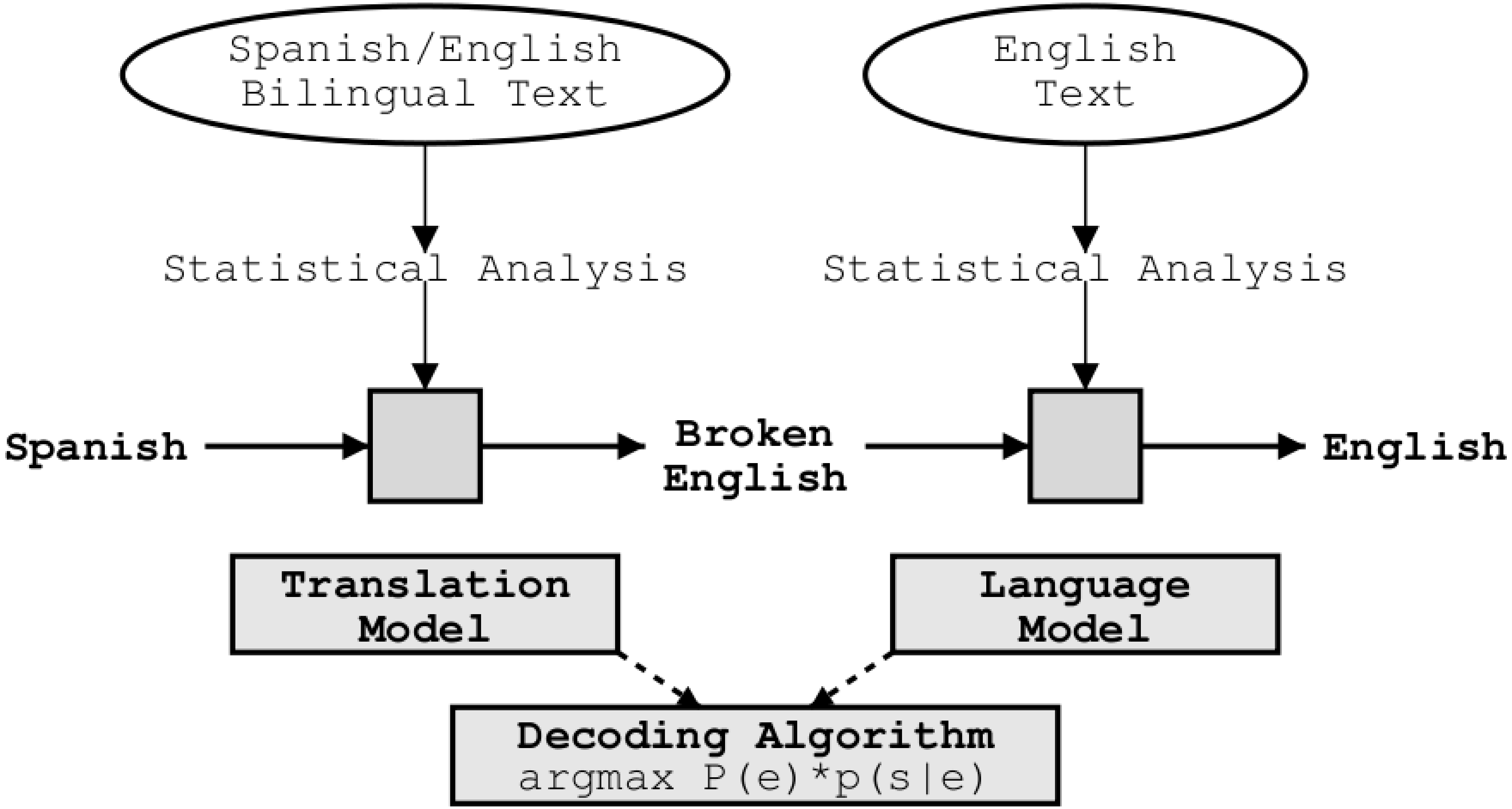
MOTIVATION IN 21ST CENTURY

- translation of web pages for gisting (getting the main message)
- methods for speeding-up human translation substantially (translation memories)
- cross-language extraction of facts and search for information
- instant translation of e-communication
- translation on mobile devices

RULE-BASED MT

STATISTICAL MACHINE TRANSLATION

SMT SCHEME



Spanish/English
Bilingual Text
English
Text
Statistical Analysis
Statistical Analysis
Spanish
Broken
English
English
Translation
Model
Language
Model
Decoding Algorithm
argmax P(e)*p(s|e)

PARALLEL CORPORA I

- basic data source for SMT
- available sources ~10–100 M
- size depends heavily on a language pair
- multilingual webpages (online newspapers)
- paragraph and sentence alignment needed

PARALLEL CORPORA II

- Europarl: 11 ls, 40 M words
- OPUS: parallel texts of various origin, open subtitles, UI localizations
- Acquis Communautaire: law documents of EU (20 ls)
- Hansards: 1.3 M pairs of text chunks from the official records of the Canadian Parliament
- EUR-Lex
- comparable corpora...

SENTENCE ALIGNMENT

- sometimes sentences are not in 1:1 ratio in corpora
- Church-Gale alignment
- hunalign

P	alignment
0.89	1:1
0.0099	1:0, 0:1
0.089	2:1, 1:2
0.011	2:2

SMT NOISY CHANNEL PRINCIPLE

Claude Shannon (1948), self-correcting codes transfered through noisy channels based on information about the original data and errors made in the channels.

Used for MT, ASR, OCR. Optical Character Recognition is erroneous but we can estimate what was damaged in a text (with a language model); errors l↔1↔I, rn↔m etc.

$$\begin{aligned} e^* &= \arg\max_e p(e|f) \\ &= \arg\max_e \frac{p(e)p(f|e)}{p(f)} \\ &= \arg\max_e p(e)p(f|e) \end{aligned}$$

SMT COMPONENTS I

- language model
- how we get $p(e)$ for any string e
- the more e looks like proper language the higher $p(e)$ should be
- issue: what is $p(e)$ for an unseen e?

SMT COMPONENTS II

- translation model
- for e and f compute $p(f|e)$
- the more e looks like a proper translation of f, the higher $p(f|e)$

SMT COMPONENTS III

- decoding algorithm
- based on TM and LM, find a sentence f as the best translation of e
- as fast as possible and with as few memory as possible
- prune non-perspective hypotheses
- but do not lost any valid translations

LANGUAGE MODELS

WHAT IT IS GOOD FOR?

What is the probability of utterance of $\boldsymbol{s}$?

I go to home vs. *I go home*

What is the next, most probable word?

Ke snídani jsem měl celozrnný ...

{ chléb $>$ pečivo $>$ zákusek $>$ mléko $>$ babičku}

CHOMSKY WAS WRONG

Colorless green ideas sleep furiously
vs. *Furiously sleep ideas green colorless*

LM assigns higher $\boldsymbol{p}$ to the 1st! (Mikolov, 2012)

GENERATING RANDOM TEXT

To him swallowed confess hear both. Which. Of save on trail for are ay device and rote life have Every enter now severally so, let. (unigrams)

Sweet prince, Falstaff shall die. Harry of Monmouth's grave. This shall forbid it should be branded, if renown made it empty. (trigrams)

Can you guess the author of the original text?

CBLM

MAXIMUM LIKELIHOOD ESTIMATION

$$p(w_3|w_1, w_2) = \frac{count(w_1, w_2, w_3)}{\sum_w count(w_1, w_2, w)}$$

(the, green, *): 1,748× in EuroParl

w	count	p(w)
paper	801	0.458
group	640	0.367
light	110	0.063
party	27	0.015
ecu	21	0.012

LM QUALITY

We need to compare quality of various LMs.

2 approaches: extrinsic and intrinsic evaluation.

A good LM should assign a higher probability to a good (looking) text than to an incorrect text. For a fixed testing text we can compare various LMs.

ENTROPY

- Shannon, 1949
- the expected value (average) of the information contained in a message
- information viewed as the negative of the logarithm of the probability distribution
- events that always occur do not communicate information
- pure randomness has highest entropy (uniform distribution $log_2 n$)

$$E(X) = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i)$$

PERPLEXITY

$$PP = 2^{H(p_{LM})}$$

$$PP(W) = p(w_1 w_2 \ldots w_n)^{-\frac{1}{N}}$$

A good LM should not waste $\boldsymbol{p}$ for improbable phenomena. The lower entropy, the better $\longrightarrow$ the lower perplexity, the better.

Minimizing probabilities = minimizing perplexity.

WHAT INFLUENCES LM QUALITY?

- size of training data
- order of language model
- smoothing, interpolation, back-off

LARGE LM - N-GRAM COUNTS

How many unique n-grams are in a corpus?

order	**types**	**singletons**	**%**
unigram	86,700	33,447	(38,6%)
bigram	1,948,935	1,132,844	(58,1%)
trigram	8,092,798	6,022,286	(74,4%)
4-gram	15,303,847	13,081,621	(85,5%)
5-gram	19,882,175	18,324,577	(92,2%)

Taken from Europarl with 30 mil. tokens.

ZERO FREQUENCY, OOV, RARE WORDS

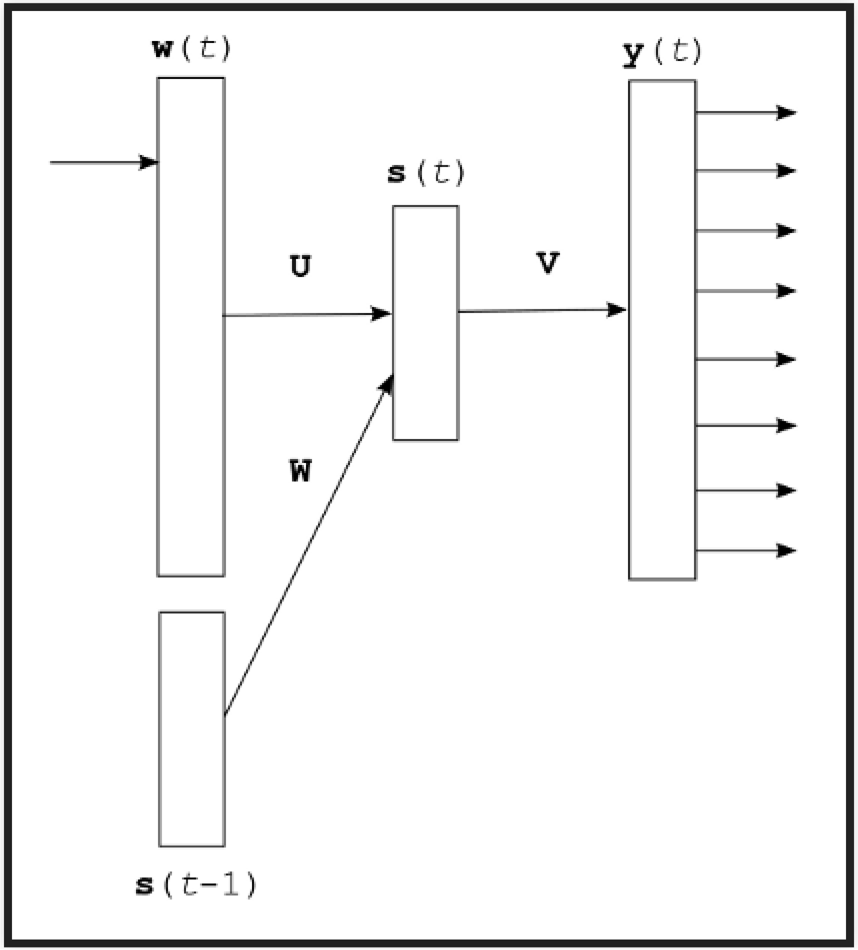
- probability must always be non zero
- to be able to measure perplexity
- maximum likelihood bad at it
- training data: work on Tuesday/Friday/Wednesday
- test data: work on Sunday,
  $p(Sunday|work\ on) = 0$

NEURAL NETWORK LANGUAGE MODELS

- old approach (1940s)
- only recently applied successfully to LM
- 2003 Bengio et al. (feed-forward NNLM)
- 2012 Mikolov (RNN)
- trending right now
- key concept: distributed representations of words
- 1-of-V, one-hot representation

RECURRENT NEURAL NETWORK

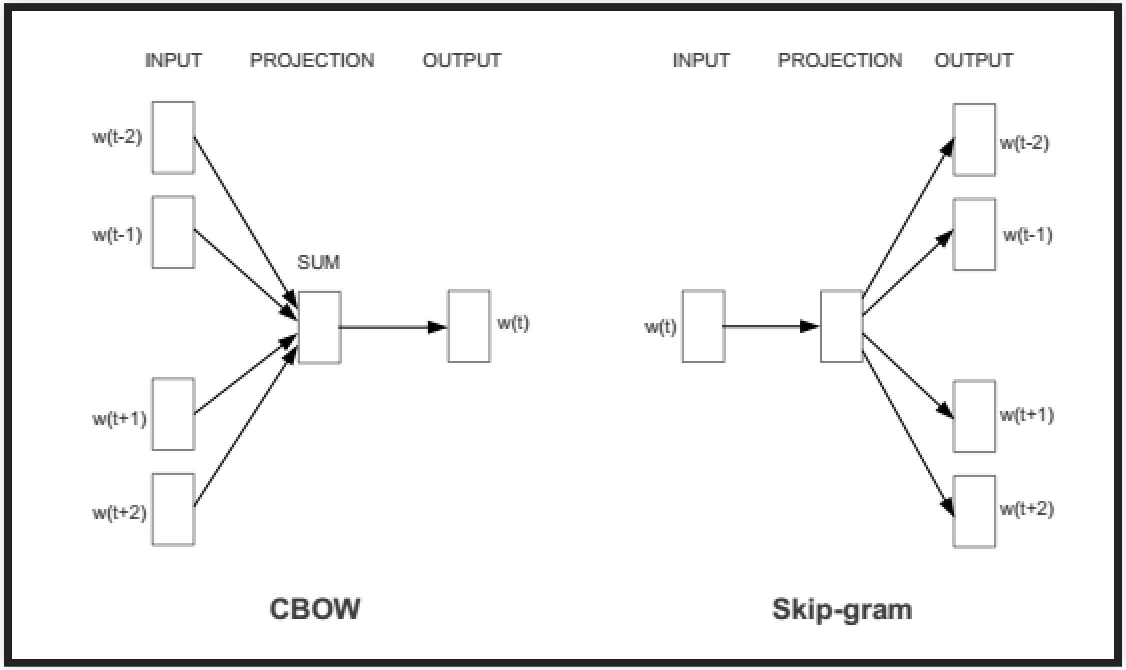
- Tomáš Mikolov (VUT)
- hidden layer feeds itself
- shown to beat n-grams by large margin

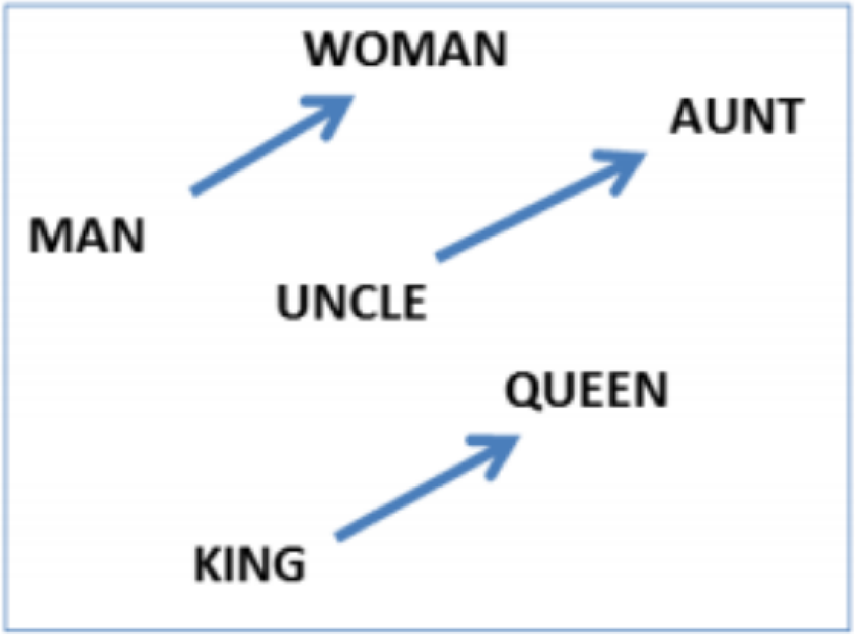
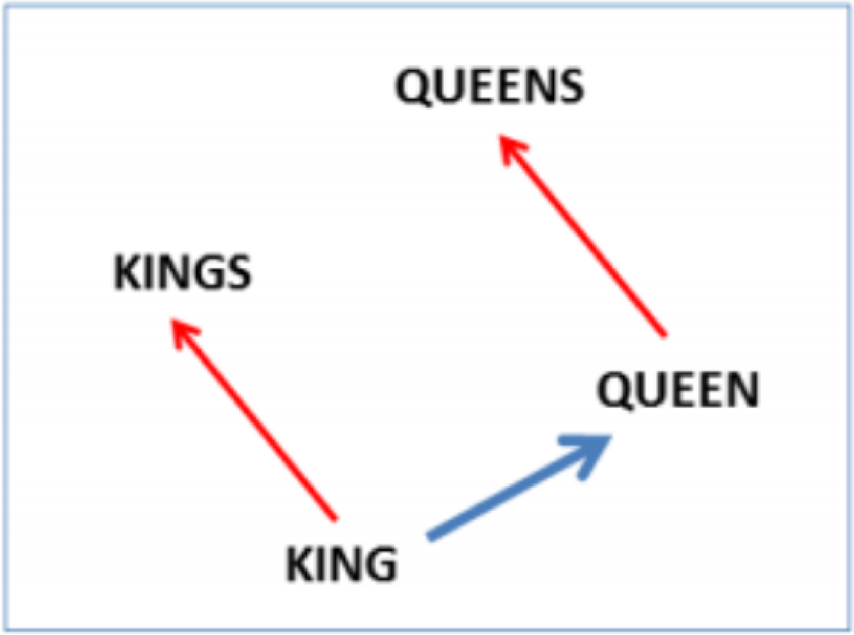


Model	Num. Params [billions]	Training Time		Perplexity
		[hours]	[CPUs]	
Interpolated KN 5-gram, 1.1B n-grams (KN)	1.76	3	100	67.6
Katz 5-gram, 1.1B n-grams	1.74	2	100	79.9
Stupid Backoff 5-gram (SBO)	1.13	0.4	200	87.9
Interpolated KN 5-gram, 15M n-grams	0.03	3	100	243.2
Katz 5-gram, 15M n-grams	0.03	2	100	127.5
Binary MaxEnt 5-gram (n-gram features)	1.13	1	5000	115.4
Binary MaxEnt 5-gram (n-gram + skip-1 features)	1.8	1.25	5000	107.1
Hierarchical Softmax MaxEnt 4-gram (HME)	6	3	1	101.3
Recurrent NN-256 + MaxEnt 9-gram	20	60	24	58.3
Recurrent NN-512 + MaxEnt 9-gram	20	120	24	54.5
Recurrent NN-1024 + MaxEnt 9-gram	20	240	24	51.3

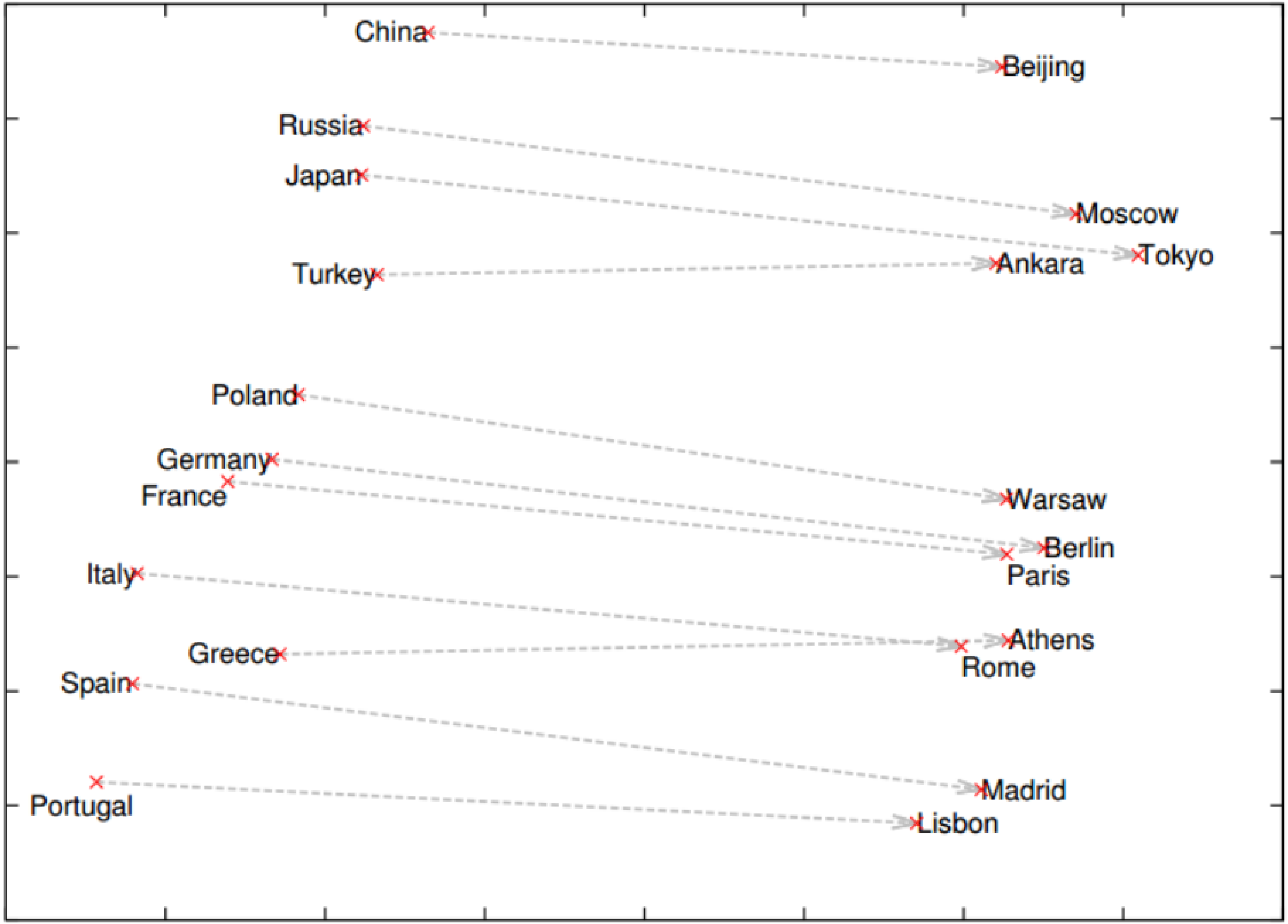
WORD EMBEDDINGS

- distributional semantics with vectors
- skip-gram, CBOW (continuous bag-of-words)

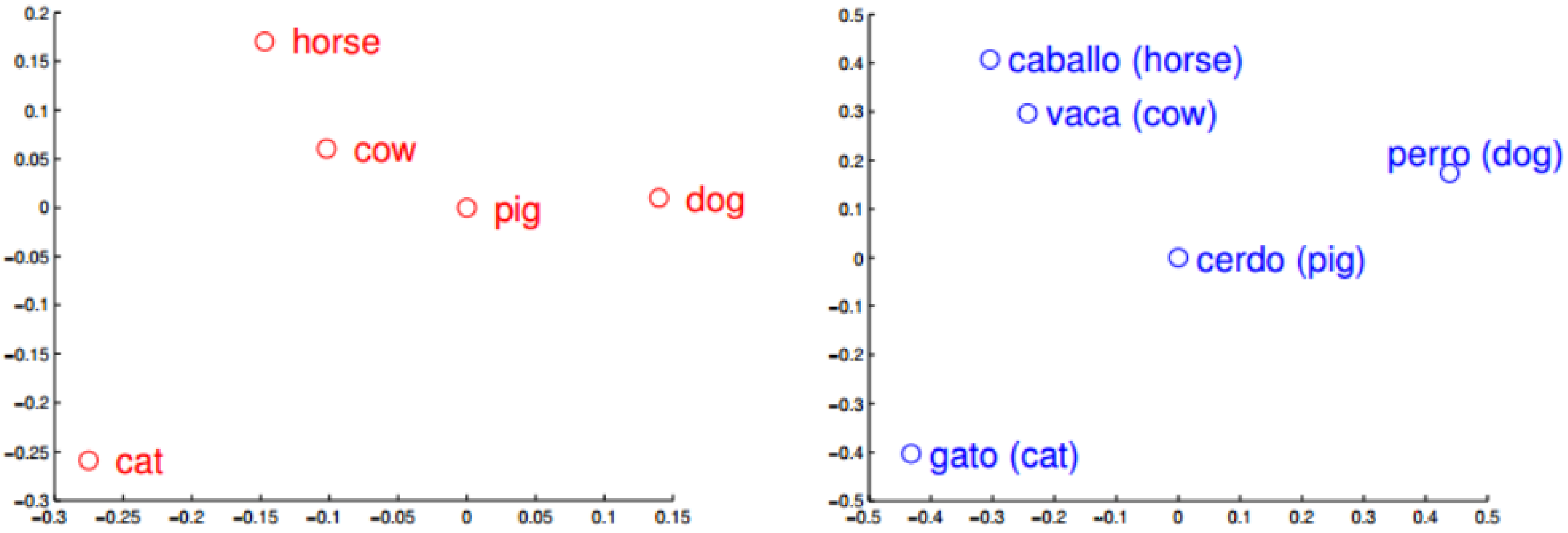



WOMAN
AUNT
MAN
UNCLE
QUEEN
KING

QUEENS
KINGS
QUEEN
KING

Expression	*Nearest token*
Paris - France + Italy	Rome
bigger - big + cold	colder
sushi - Japan + Germany	bratwurst
Cu - copper + gold	Au
Windows - Microsoft + Google	Android
Montreal Canadiens - Montreal + Toronto	Toronto Maple Leafs


China
Beijing
Russia
Japan
Moscow
Tokyo
Turkey
Ankara
Poland
Germany
France
Warsaw
Berlin
Paris
Italy
Greece
Athens
Rome
Spain
Portugal
Madrid
Lisbon

EMBEDDINGS IN MT



TRANSLATION MODELS

LEXICAL TRANSLATION

Standard lexicon does not contain information about frequency of translations of individual meanings of words.

key → klíč, tónina, klávesa

How often are the individual translations used in translations?

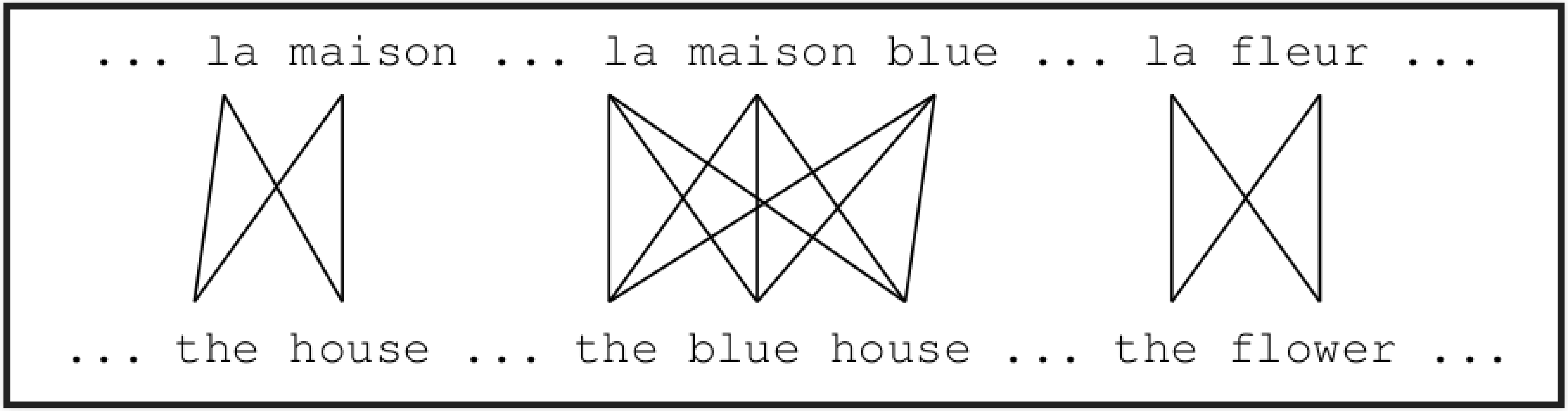
key → klíč (0.7), tónina (0.18), klávesa (0.11)

probability distribution p_f:

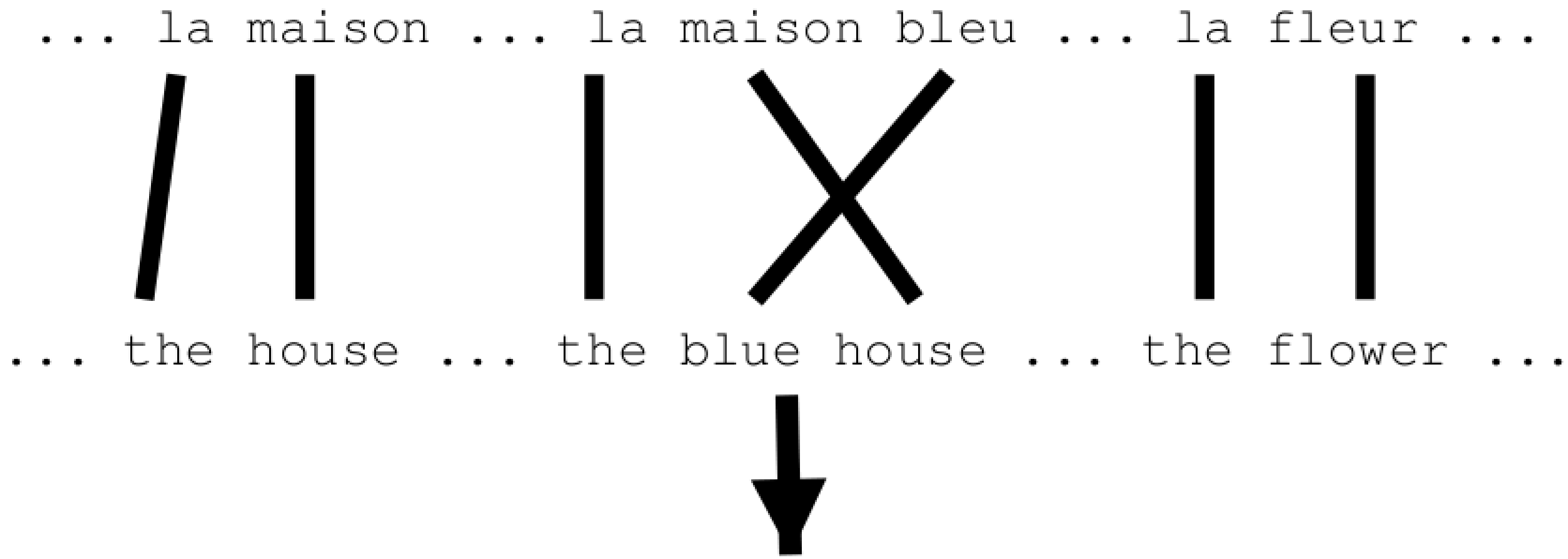
$$\sum_e p_f(e) = 1$$

$$\forall e : 0 \leq p_f(e) \leq 1$$

EM ALGORITHM - INITIALIZATION



EM ALGORITHM - FINAL PHASE



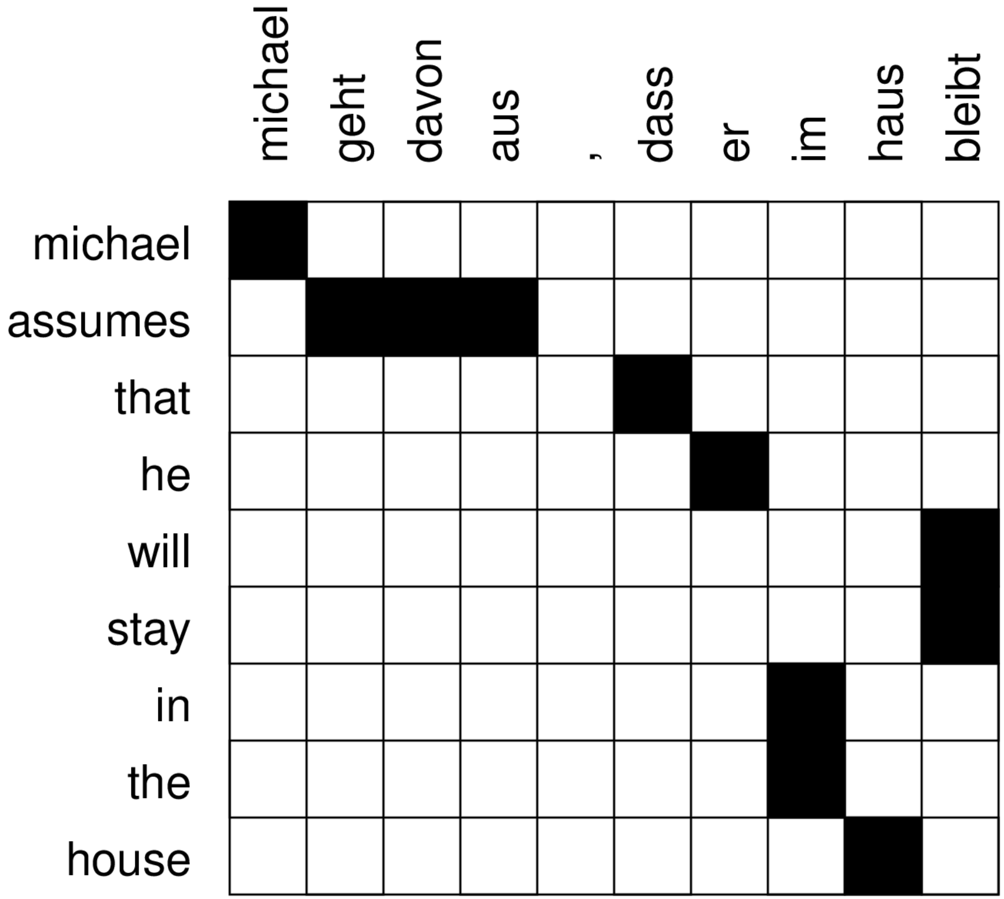
p(la|the) = 0.453
p(le|the) = 0.334
p(maison|house) = 0.876
p(bleu|blue) = 0.563
...

IBM MODELS

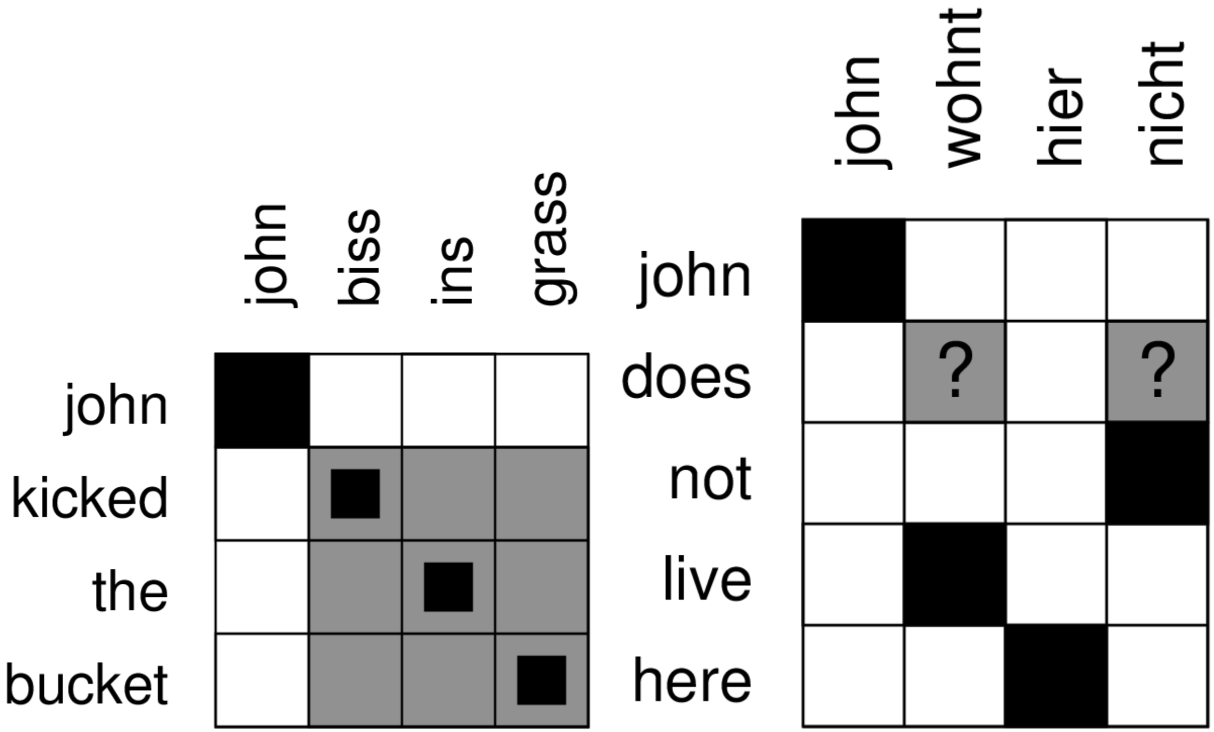
IBM-1 does not take context into account, cannot add and skip words. Each of the following models adds something more to the previous.

- IBM-1: lexical translation
- IBM-2: + absolute alignment model
- IBM-3: + *fertility* model
- IBM-4: + relative alignment model
- IBM-5: + further tuning

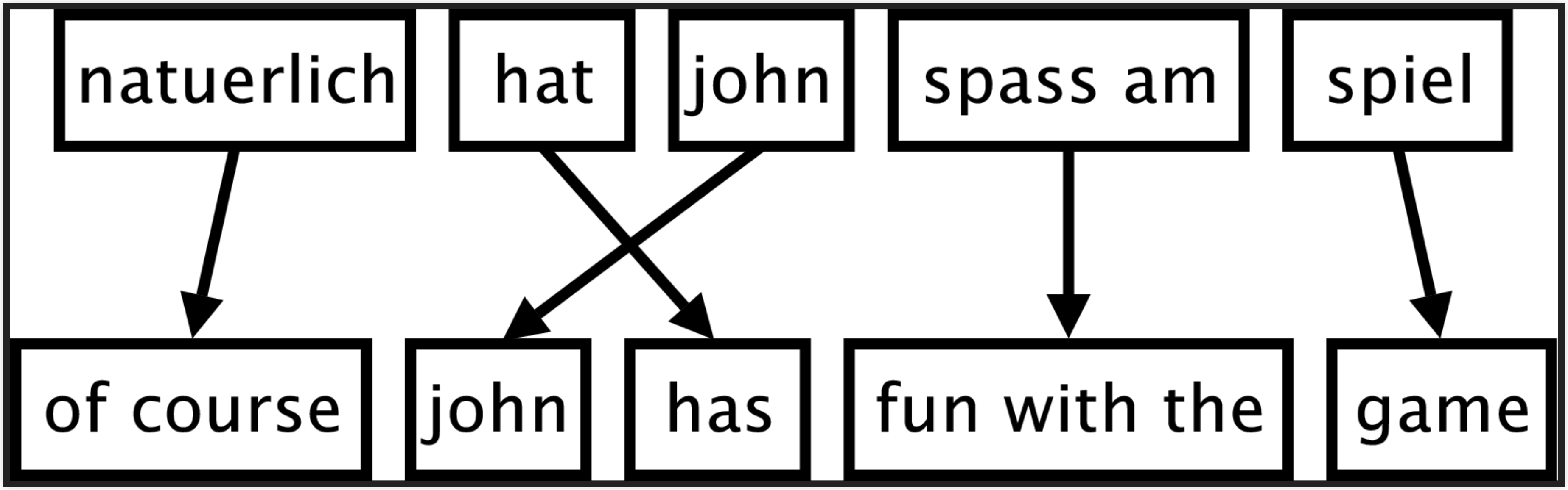
WORD ALIGNMENT MATRIX



WORD ALIGNMENT ISSUES



PHRASE-BASE TRANSLATION MODEL

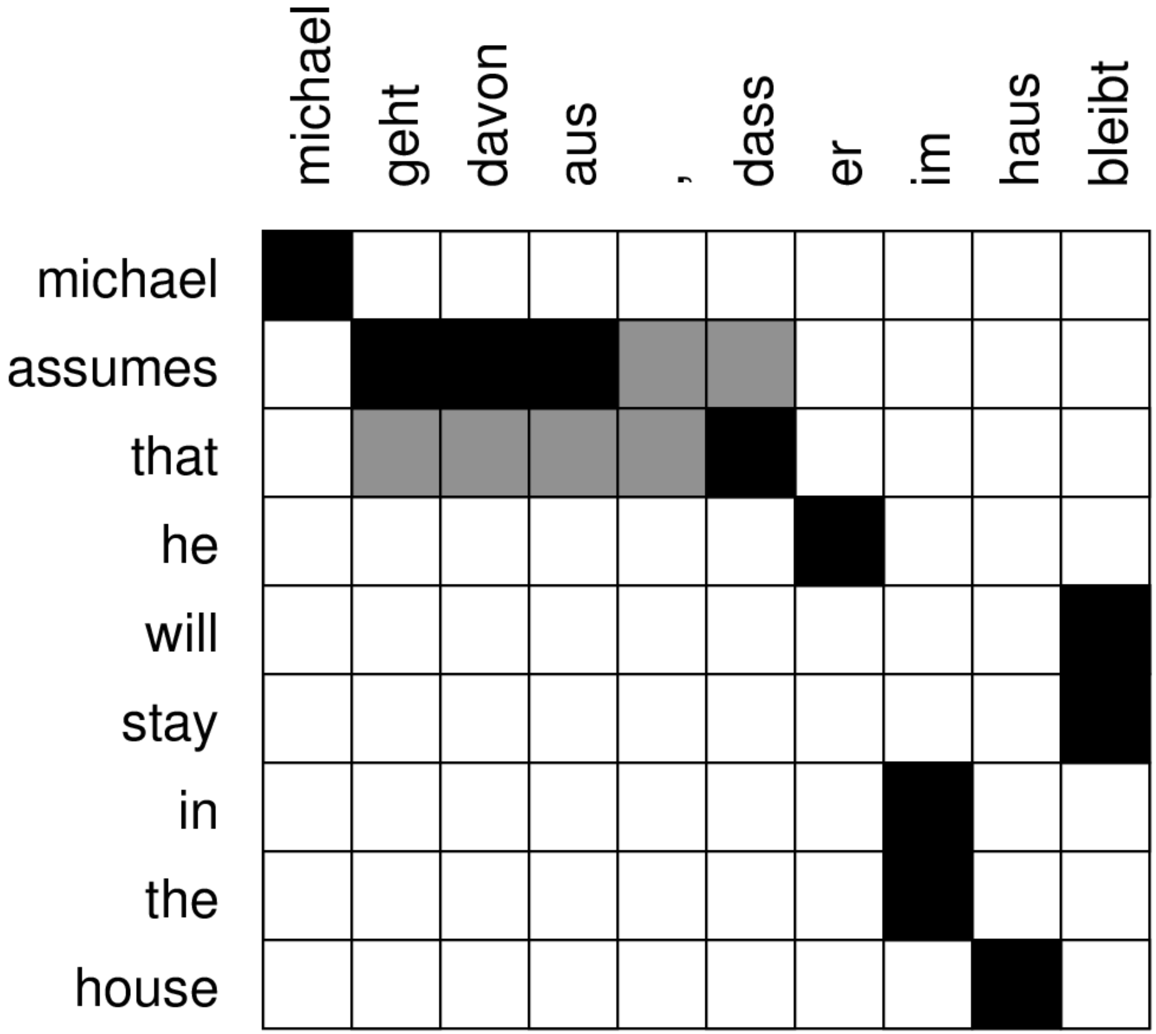


Phrases not linguistically, but statistically motivated.
German *am* is seldom translated with single English *to*.
Cf. (fun (with (the game)))

ADVANTAGES OF PBTM

- translating n:m words
- word is not a suitable element for translation for many lang. pairs
- models learn to translate longer phrases
- simpler: no fertility, no NULL token etc.

PHRASE EXTRACTION



EXTRACTED PHRASES

phr1	phr2
michael	michael
assumes	geht davon aus / geht davon aus
in the	im
house	haus
assumes that	geht davon aus , dass
that he	dass er / , dass er
in the house	im haus

PHRASE-BASED MODEL OF SMT

$$e^* = \mathrm{argmax}_e \prod_{i=1}^{I} \phi(\bar{f}_i|\bar{e}_i)\ d(start_i - end_{i-1} - 1)$$

$$\prod_{i=1}^{|\mathbf{e}|} p_{LM}(e_i|e_1 \ldots e_{i-1})$$

DECODING

Given a model p_{LM} and translation model $p(f|e)$ we need to find a translation with the highest probability but from exponential number of all possible translations.

Heuristic search methods are used. It is not guaranteed to find the best translation.

Errors in translations are caused by
1) decoding process, when the best translation is not found owing to the heuristics or
2) models, where the best translation according to the probability functions is not the best possible.

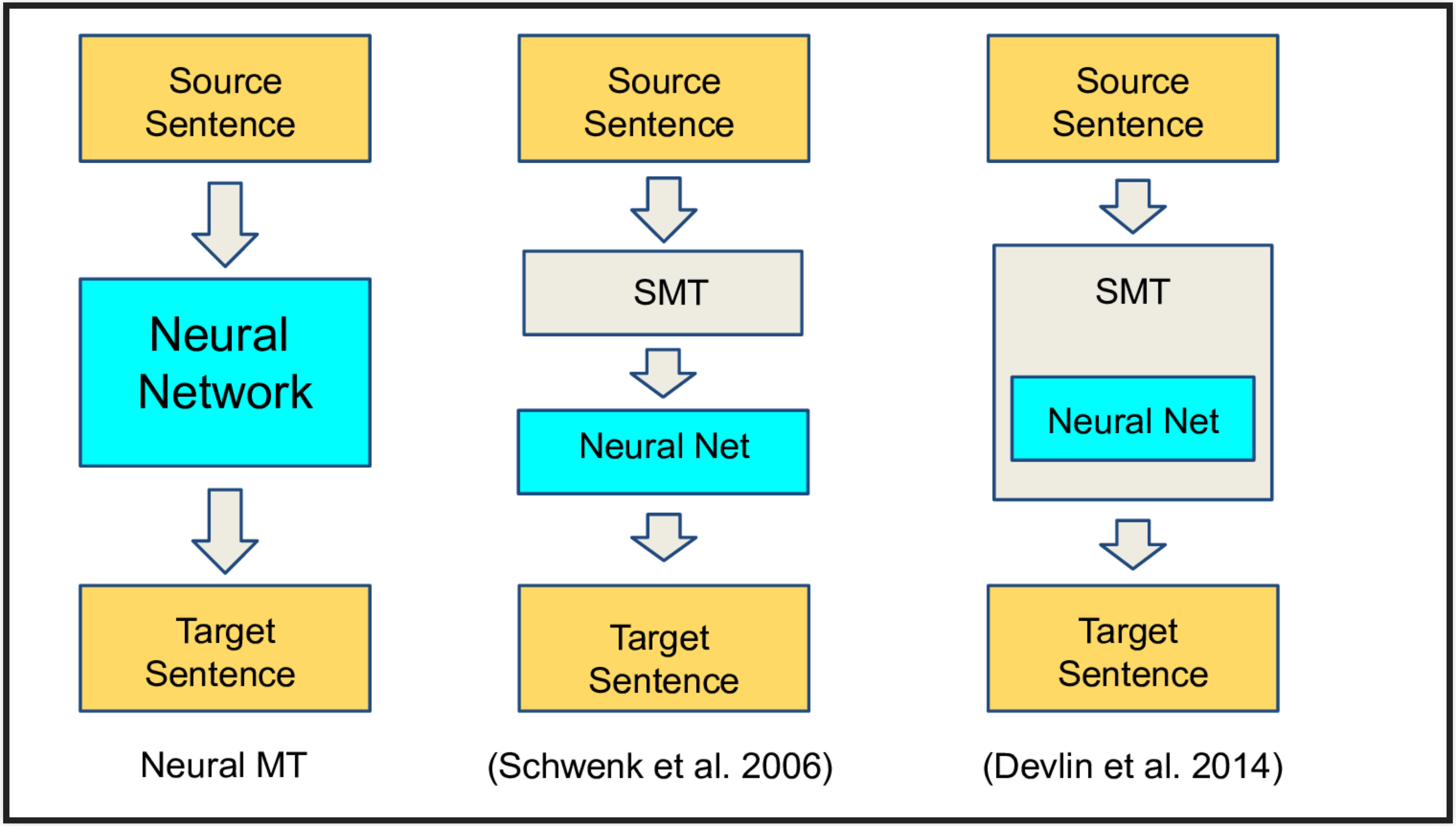
EXAMPLE OF NOISE-INDUCED ERRORS (GOOGLE TRANSLATE)

- Rinneadh clárúchán an úsáideora *yxc* a eiteach go rathúil.
- The user registration *yxc* made a successful rejection.
- Rinneadh clárúchán an úsáideora *qqq* a eiteach go rathúil.
- *Qqq* made registration a user successfully refused.

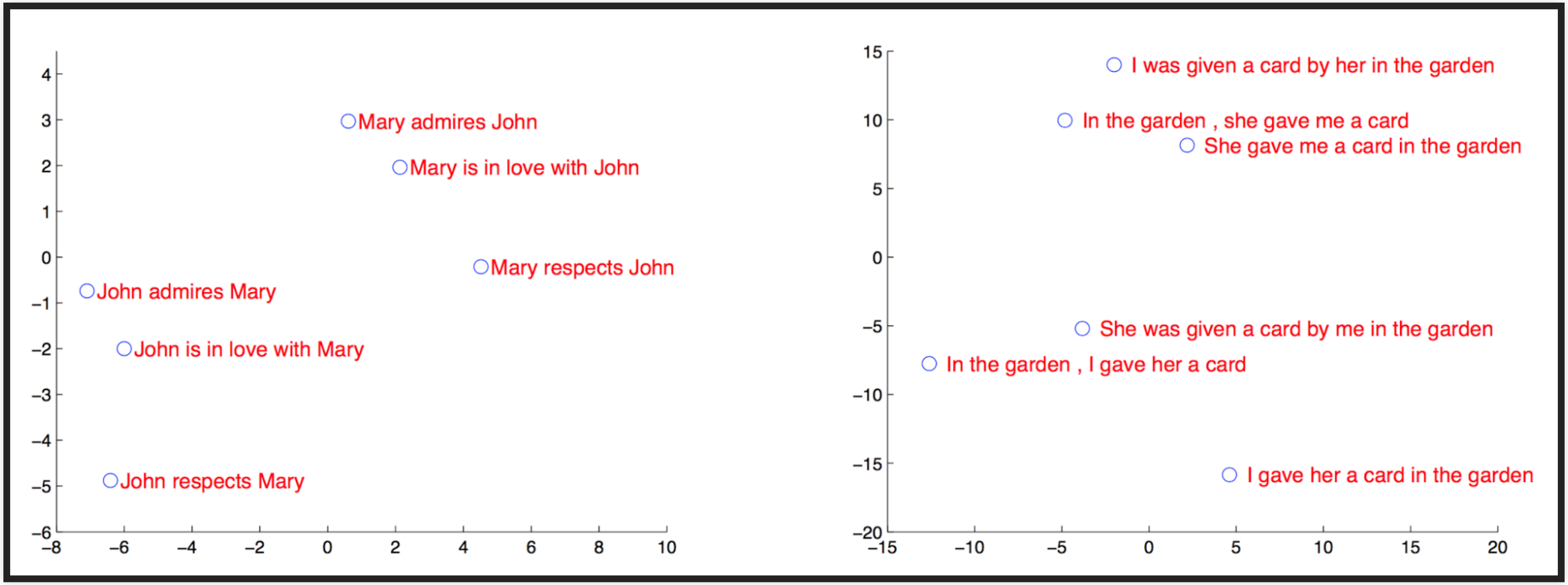
NEURAL NETWORK MACHINE TRANSLATION

- very close to state-of-the-art (PBSMT)
- a problem: variable length input and output
- learning to translate and align at the same time
- LISA
- hot topic (2014, 2015)

NN MODELS IN MT



SUMMARY VECTOR FOR SENTENCES



MT QUALITY EVALUATION

fluency, adequacy, intelligibility

AUTOMATIC TRANSLATION EVALUATION

- advantages: speed, cost
- disadvantages: do we really measure quality of translation?
- gold standard: manually prepared reference translations
- candidate $\boldsymbol{c}$ is compared with $\boldsymbol{n}$ reference translations $\boldsymbol{r_i}$
- the paradox of automatic evaluation: the task corresponds to situation where students are to assess their own exam: how they know where they made a mistake?
- various approaches: n-gram shared between $\boldsymbol{c}$ and $\boldsymbol{r_i}$, edit distance, ...

RECALL AND PRECISION ON WORDS

SYSTEM A: Israeli officials ~~responsibility~~ ~~of~~ airport ~~safety~~

REFERENCE: Israeli officials are responsible for airport security

$$\text{precision} = \frac{\text{correct}}{\text{output-length}} = \frac{3}{6} = 50\%$$

$$\text{recall} = \frac{\text{correct}}{\text{reference-length}} = \frac{3}{7} = 43\%$$

$$\text{f-score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} = 2 \times \frac{.5 \times .43}{.5 + .43} = 46\%$$

RECALL AND PRECISION: SHORTCOMINGS

metrics	system A	system B
precision	50%	100%
recall	43%	100%
f-score	46%	100%

It does not capture wrong word order.

BLEU

- standard metrics (2001)
- IBM, Papineni
- n-gram match between reference and candidate translations
- precision is calculated for 1-, 2- ,3- and 4-grams
- + **brevity penalty**

$$\text{BLEU} = \min\left(1, \frac{\text{output-length}}{\text{reference-length}}\right) \Big(\prod_{i=1}^{4} \text{precisio}$$

BLEU: AN EXAMPLE

SYSTEM A: Israeli officials responsibility of airport safety
2-GRAM MATCH (Israeli officials) · 1-GRAM MATCH (airport)

REFERENCE: Israeli officials are responsible for airport security

SYSTEM B: airport security Israeli officials are responsible
2-GRAM MATCH (airport security) · 4-GRAM MATCH (Israeli officials are responsible)

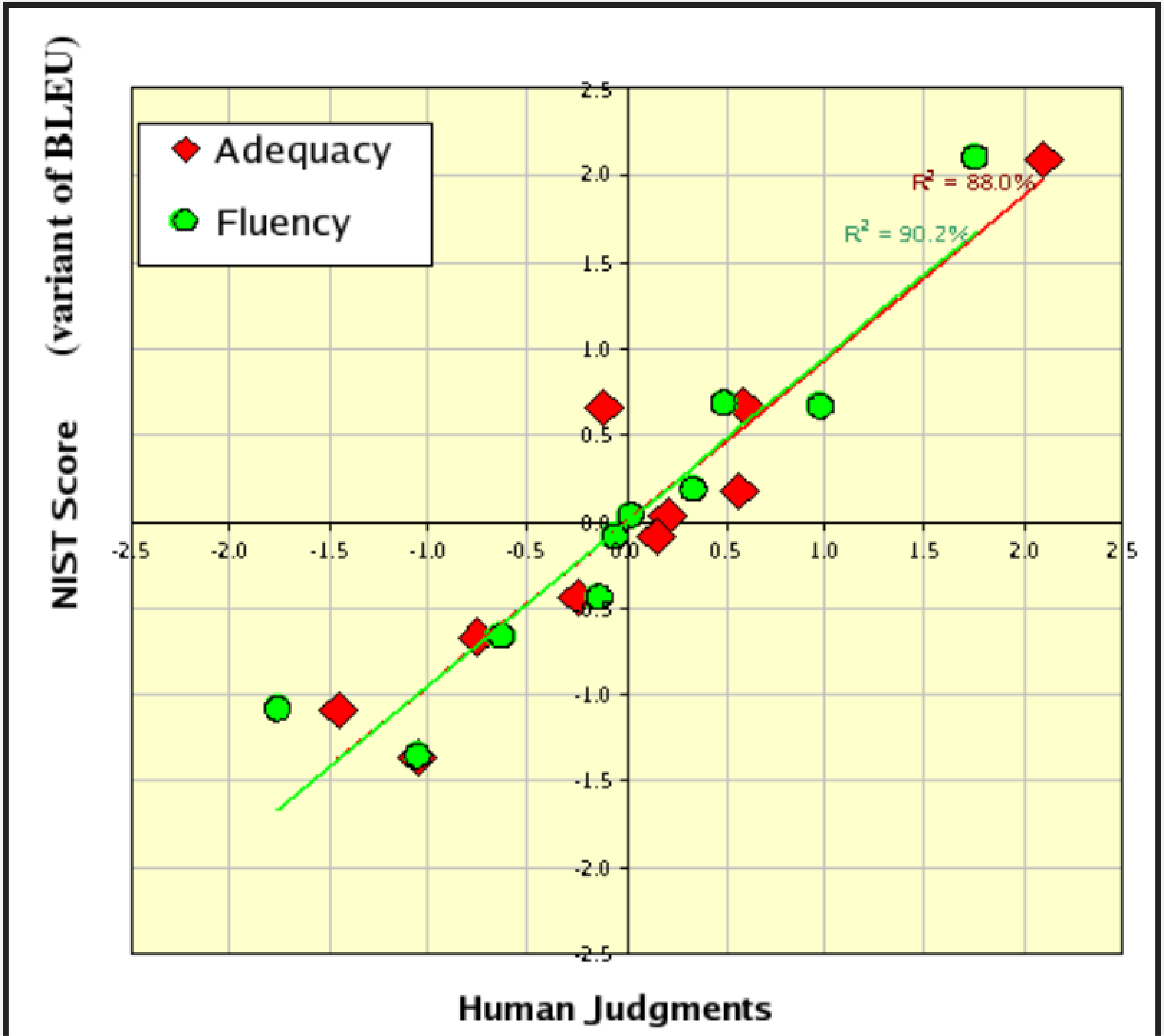
metrics	system A	system B
precision (1gram)	3/6	6/6
precision (2gram)	1/5	4/5
precision (3gram)	0/4	2/4
precision (4gram)	0/3	1/3
brevity penalty	6/7	6/7
BLEU	0%	52%

METEOR

- aligns hypotheses to one or more references
- exact, stem (morphology), synonym (WordNet), paraphrase matches
- various scores including WMT ranking and NIST adequacy
- extended support for English, Czech, German, French, Spanish, and Arabic.
- high correlation with human judgments

EVALUATION OF EVALUATION METRICS

Correlation of automatic evaluation with manual evaluation.


(variant of BLEU)
NIST Score
Adequacy
Fluency
R² = 88.0%
R² = 90.2%
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
-2.0
-2.5
2.5
Human Judgments

EUROMATRIX

EURO MATRIX

output language

input language

Danish	BLEU 21.47	BLEU 18.49	BLEU 21.12	BLEU 28.57	BLEU 14.24	BLEU 28.79	BLEU 22.22	BLEU 24.32	BLEU 26.49	BLEU 28.33
BLEU 20.51	Dutch	BLEU 18.39	BLEU 17.49	BLEU 23.01	BLEU 10.34	BLEU 24.67	BLEU 20.07	BLEU 20.71	BLEU 22.95	BLEU 19.03
BLEU 22.35	BLEU 23.40	German	BLEU 20.75	BLEU 25.36	BLEU 11.88	BLEU 27.75	BLEU 21.36	BLEU 23.28	BLEU 25.49	BLEU 20.51
BLEU 22.79	BLEU 20.02	BLEU 17.42	Greek	BLEU 27.28	BLEU 11.44	BLEU 32.15	BLEU 26.84	BLEU 27.67	BLEU 31.26	BLEU 21.23
BLEU 25.24	BLEU 21.02	BLEU 17.64	BLEU 23.23	English	BLEU 13.00	BLEU 31.16	BLEU 25.39	BLEU 27.10	BLEU 30.16	BLEU 24.83
BLEU 20.02	BLEU 17.09	BLEU 14.57	BLEU 18.20	BLEU 21.86	Finnish	BLEU 22.49	BLEU 18.39	BLEU 19.14	BLEU 21.16	BLEU 18.85
BLEU 23.73	BLEU 21.13	BLEU 18.54	BLEU 26.13	BLEU 30.00	BLEU 12.63	French	BLEU 32.48	BLEU 35.37	BLEU 38.47	BLEU 22.68
BLEU 21.47	BLEU 20.07	BLEU 16.92	BLEU 24.83	BLEU 27.89	BLEU 11.08	BLEU 36.09	Italian	BLEU 31.20	BLEU 34.04	BLEU 20.26
BLEU 23.27	BLEU 20.23	BLEU 18.27	BLEU 26.46	BLEU 30.11	BLEU 11.99	BLEU 39.04	BLEU 32.07	Portuguese	BLEU 37.95	BLEU 21.96
BLEU 24.10	BLEU 21.42	BLEU 18.29	BLEU 28.38	BLEU 30.51	BLEU 12.57	BLEU 40.27	BLEU 32.31	BLEU 35.92	Spanish	BLEU 23.90
BLEU 30.35	BLEU 21.94	BLEU 18.97	BLEU 22.86	BLEU 30.20	BLEU 15.37	BLEU 29.77	BLEU 23.94	BLEU 25.95	BLEU 28.66	Swedish

EUROMATRIX II

	Target Language																				
	EN	BG	DE	CS	DA	EL	ES	ET	FI	FR	HU	IT	LT	LV	MT	NL	PL	PT	RO	SK	SL	SV
EN		40.5	46.8	52.6	50.0	41.0	55.2	34.8	38.6	50.1	37.2	50.4	39.6	43.4	39.8	52.3	49.2	55.0	49.0	44.7	50.7	52.0
BG	61.3		38.7	39.4	39.6	34.5	46.9	25.5	26.7	42.4	22.0	43.5	29.3	29.1	25.9	44.9	35.1	45.9	36.8	34.1	34.1	39.9
DE	53.6	26.3		35.4	43.1	32.8	47.1	26.7	29.5	39.4	27.6	42.7	27.6	30.3	19.8	50.2	30.2	44.1	30.7	29.4	31.4	41.2
CS	58.4	32.0	42.6		43.6	34.6	48.9	30.7	30.5	41.6	27.4	44.3	34.5	35.8	26.3	46.5	39.2	45.7	36.5	43.6	41.3	42.9
DA	57.6	28.7	44.1	35.7		34.3	47.5	27.8	31.6	41.3	24.2	43.8	29.7	32.9	21.1	48.5	34.3	45.4	33.9	33.0	36.2	47.2
EL	59.5	32.4	43.1	37.7	44.5		54.0	26.5	29.0	48.3	23.7	49.6	29.0	32.6	23.8	48.9	34.2	52.5	37.2	33.1	36.3	43.3
ES	60.0	31.1	42.7	37.5	44.4	39.4		25.4	28.5	51.3	24.0	51.7	26.8	30.5	24.6	48.8	33.9	57.3	38.1	31.7	33.9	43.7
ET	52.0	24.6	37.3	35.2	37.8	28.2	40.4		37.7	33.4	30.9	37.0	35.0	36.9	20.5	41.3	32.0	37.8	28.0	30.6	32.9	37.3
FI	49.3	23.2	36.0	32.0	37.9	27.2	39.7	34.9		29.5	27.2	36.6	30.5	32.5	19.4	40.6	28.8	37.5	26.5	27.3	28.2	37.6
FR	64.0	34.5	45.1	39.5	47.4	42.8	60.9	26.7	30.0		25.5	56.1	28.3	31.9	25.3	51.6	35.7	61.0	43.8	33.1	35.6	45.8
HU	48.0	24.7	34.3	30.0	33.0	25.5	34.1	29.6	29.4	30.7		33.5	29.6	31.9	18.1	36.1	29.8	34.2	25.7	25.6	28.2	30.5
IT	61.0	32.1	44.3	38.9	45.8	40.6	26.9	25.0	29.7	52.7	24.2		29.4	32.6	24.6	50.5	35.2	56.5	39.3	32.5	34.7	44.3
LT	51.8	27.6	33.9	37.0	36.8	26.5	21.1	34.2	32.0	34.4	28.5	36.8		40.1	22.2	38.1	31.6	31.6	29.3	31.8	35.3	35.3
LV	54.0	29.1	35.0	37.8	38.5	29.7	25.3	34.2	32.4	35.6	29.3	38.9	38.4		23.3	41.5	34.4	39.6	31.0	33.3	37.1	38.0
MT	72.1	32.2	37.2	37.9	38.9	33.7	48.7	26.9	25.8	42.4	22.4	43.7	30.2	33.2		44.0	37.1	45.9	38.9	35.8	40.0	41.6
NL	56.9	29.3	46.9	37.0	45.4	33.3	49.7	27.5	29.8	43.4	25.3	44.5	28.6	31.7	22.0		32.0	47.7	33.0	30.1	34.6	43.6
PL	60.8	31.5	40.2	44.2	42.1	34.2	46.2	29.2	29.0	40.0	24.5	43.2	33.2	35.6	27.9	44.8		44.1	38.2	38.2	39.8	42.1
PT	60.7	31.4	42.9	38.4	42.8	40.2	60.7	26.4	29.2	53.2	23.8	52.8	28.0	31.5	24.8	49.3	34.5		39.4	32.1	34.4	43.9
RO	60.8	33.1	38.5	37.8	40.3	35.6	50.4	24.6	26.2	46.5	25.0	44.8	28.4	29.9	28.7	43.0	35.8	48.5		31.5	35.1	39.4
SK	60.8	32.6	39.4	48.1	41.0	33.3	46.2	29.8	28.4	39.4	27.4	41.8	33.8	36.7	28.5	44.4	39.0	43.3	35.3		42.6	41.8
SL	61.0	33.1	37.9	43.5	42.6	34.0	47.0	31.1	28.8	38.2	25.7	42.3	34.6	37.3	30.0	45.9	38.2	44.1	35.8	38.9		42.7
SV	58.5	26.9	41.0	35.6	46.6	33.3	46.6	27.4	30.9	38.9	22.7	42.0	28.2	31.0	23.7	45.6	32.2	44.2	32.7	31.3	33.5	