CRF Word Alignment & Noisy Channel Translation

January 31, 2013

Last Time ...

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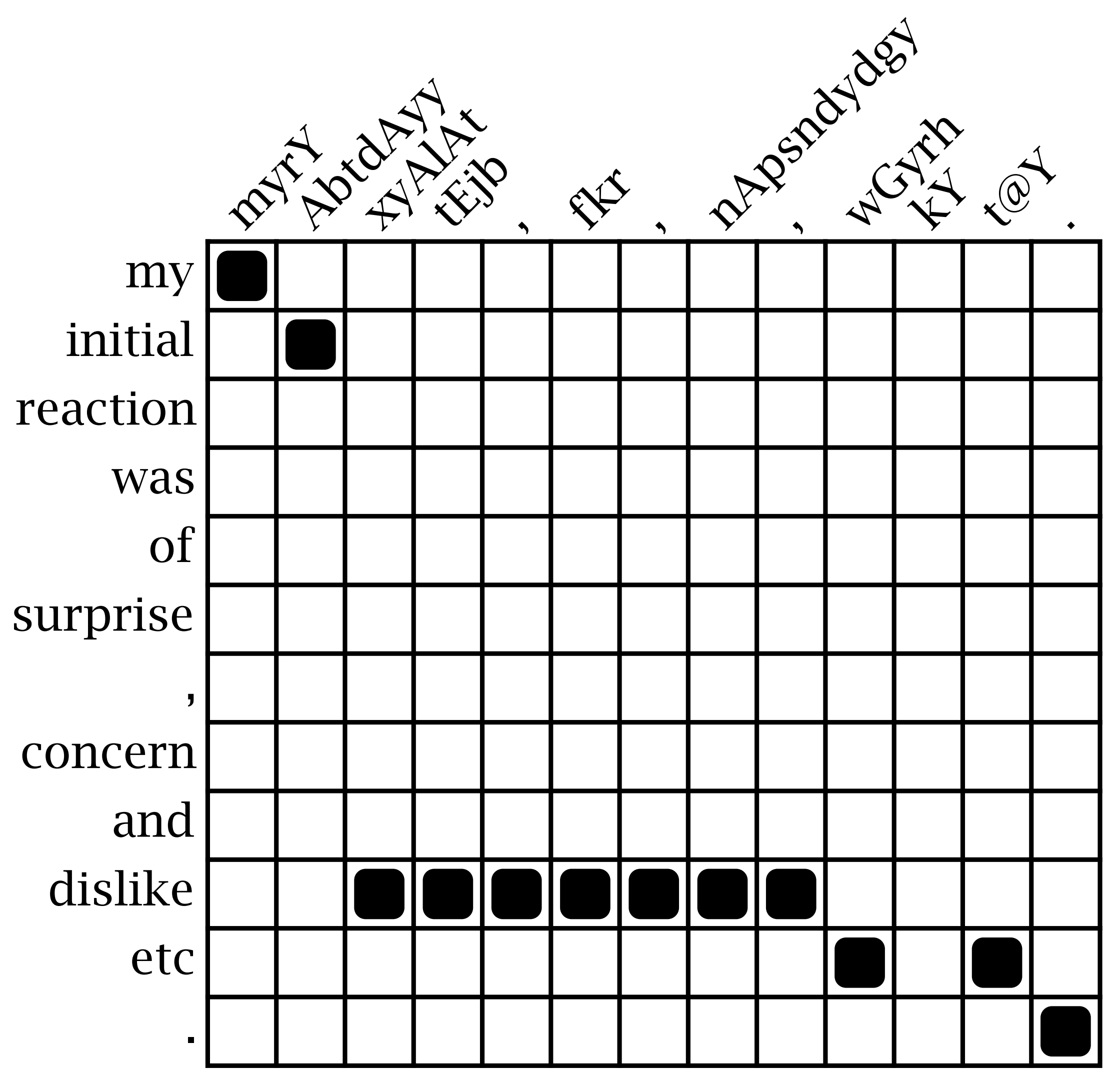
$$p(\mathbf{e} \mid \mathbf{f}, m) = \sum_{\mathbf{a} \in [0,n]^m} \overbrace{p(\mathbf{a} \mid \mathbf{f}, m)} \times \overbrace{\prod_{i=1}^{m} p(e_i \mid f_{a_i})}$$

MAP alignment



IBM Model 4 alignment

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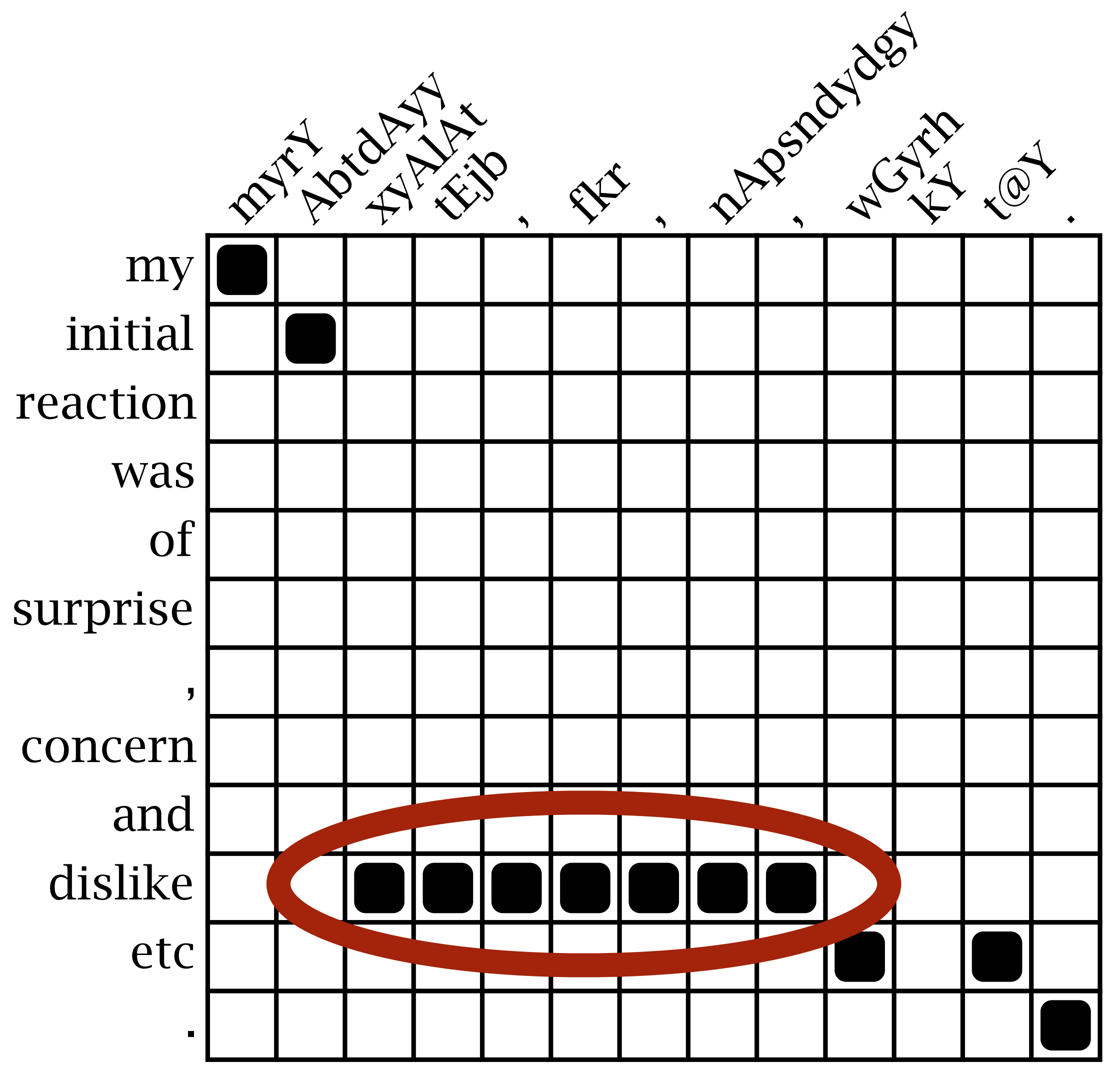
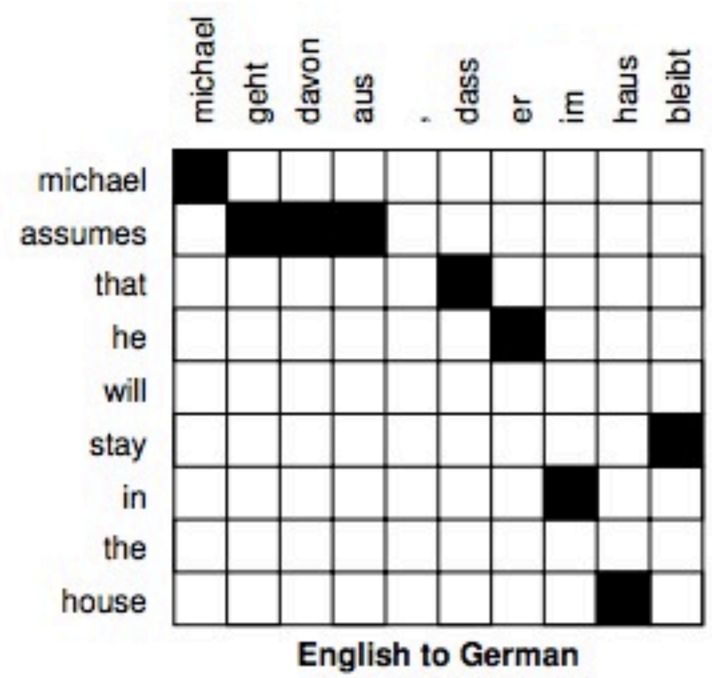


IBM Model 4 alignment

A few tricks...

p(f|e)



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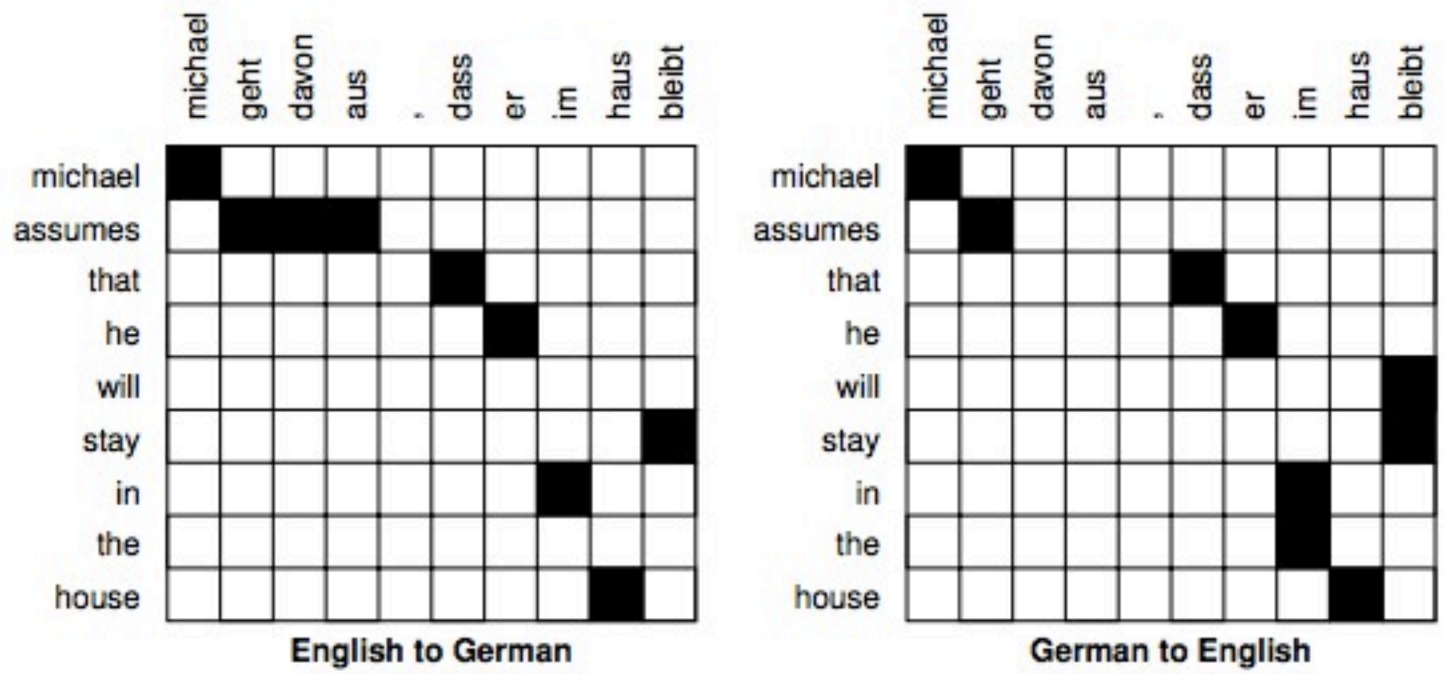

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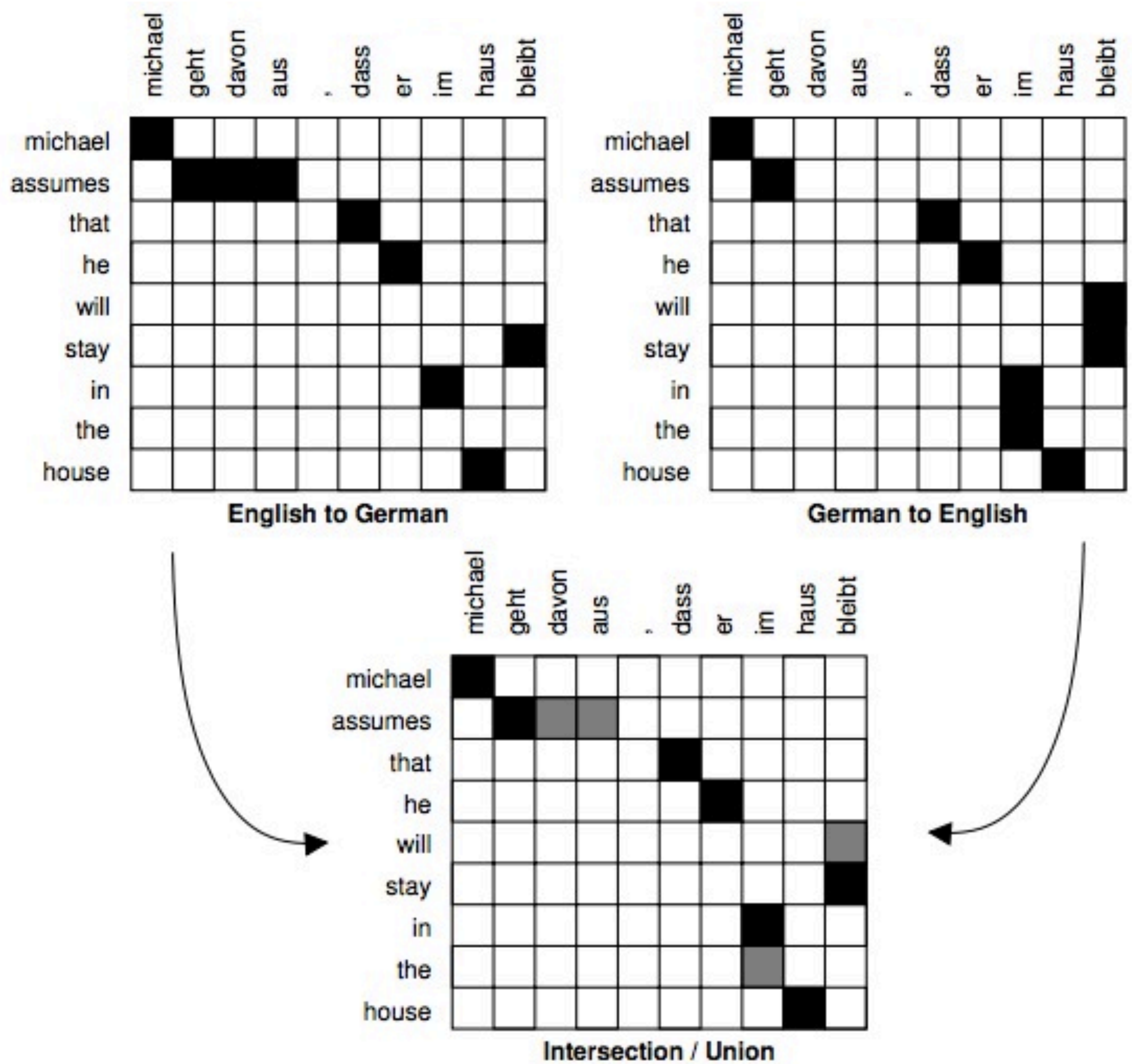

p(e|f)

Another View

With this model:

$$p(\mathbf{e} \mid \mathbf{f}, m) = \sum_{\mathbf{a} \in [0,n]^m} p(\mathbf{a} \mid \mathbf{f}, m) \times \prod_{i=1}^{m} p(e_i \mid f_{a_i})$$

The problem of word alignment is as:

$$\mathbf{a}^* = \arg \max_{\mathbf{a} \in [0,n]^m} p(\mathbf{a} \mid \mathbf{e}, \mathbf{f}, m)$$

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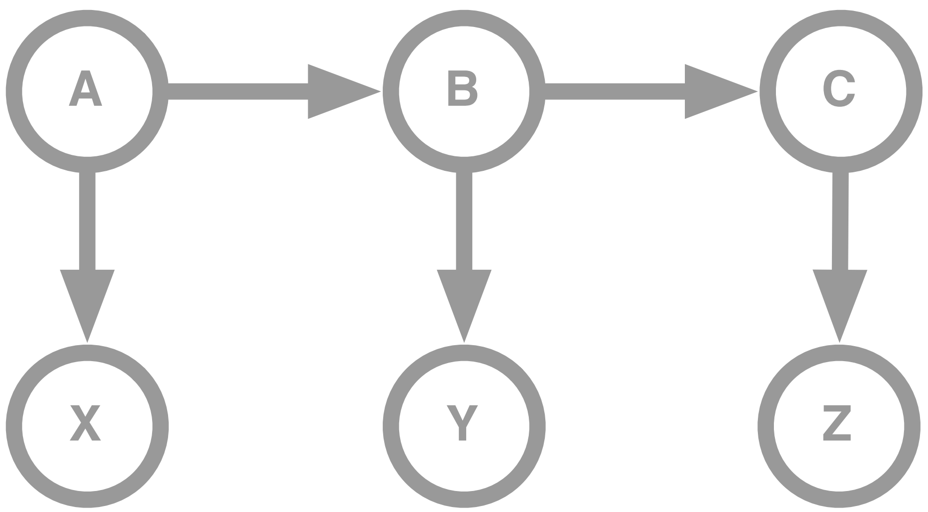
Can we model this distribution directly?

Markov Random Fields (MRFs)



$$
\begin{aligned}
&p(A,B,C,X,Y,Z) = \\
&\quad p(A) \times p(B \mid A) \times p(C \mid B) \times \\
&\quad\quad p(X \mid A) p(Y \mid B) p(Z \mid C)
\end{aligned}
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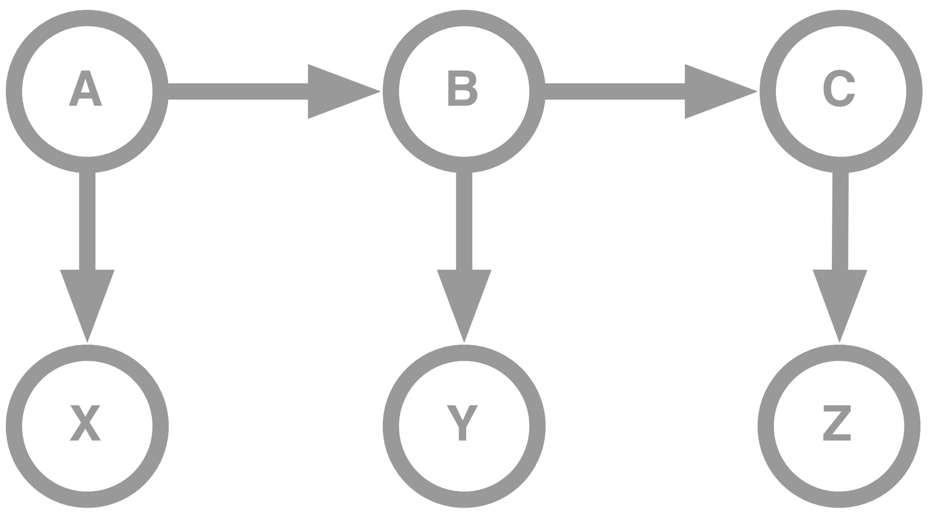
Markov Random Fields (MRFs)



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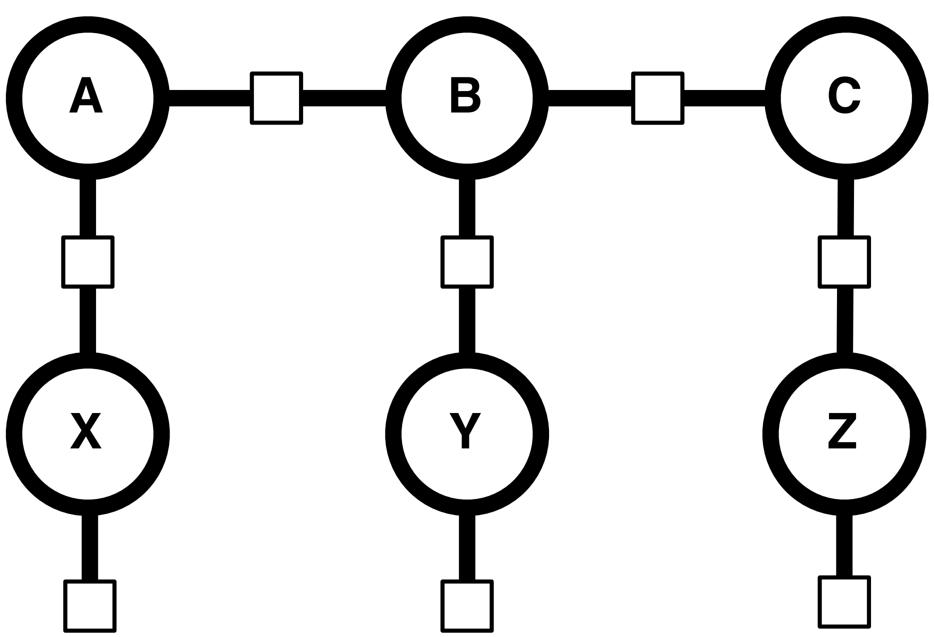

$$p(A, B, C, X, Y, Z) = \frac{1}{Z} \times$$
$$\Psi_1(A, B) \times \Psi_2(B, C) \times \Psi_3(C, D) \times$$
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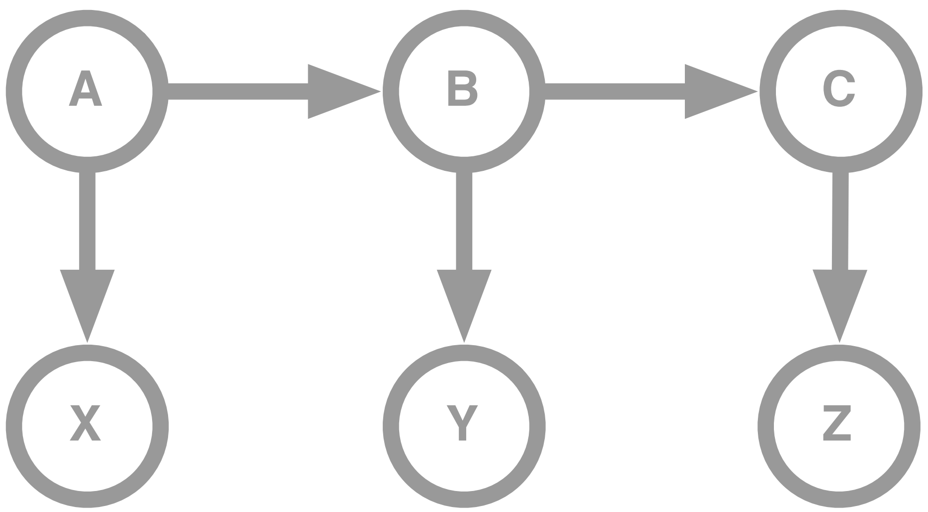

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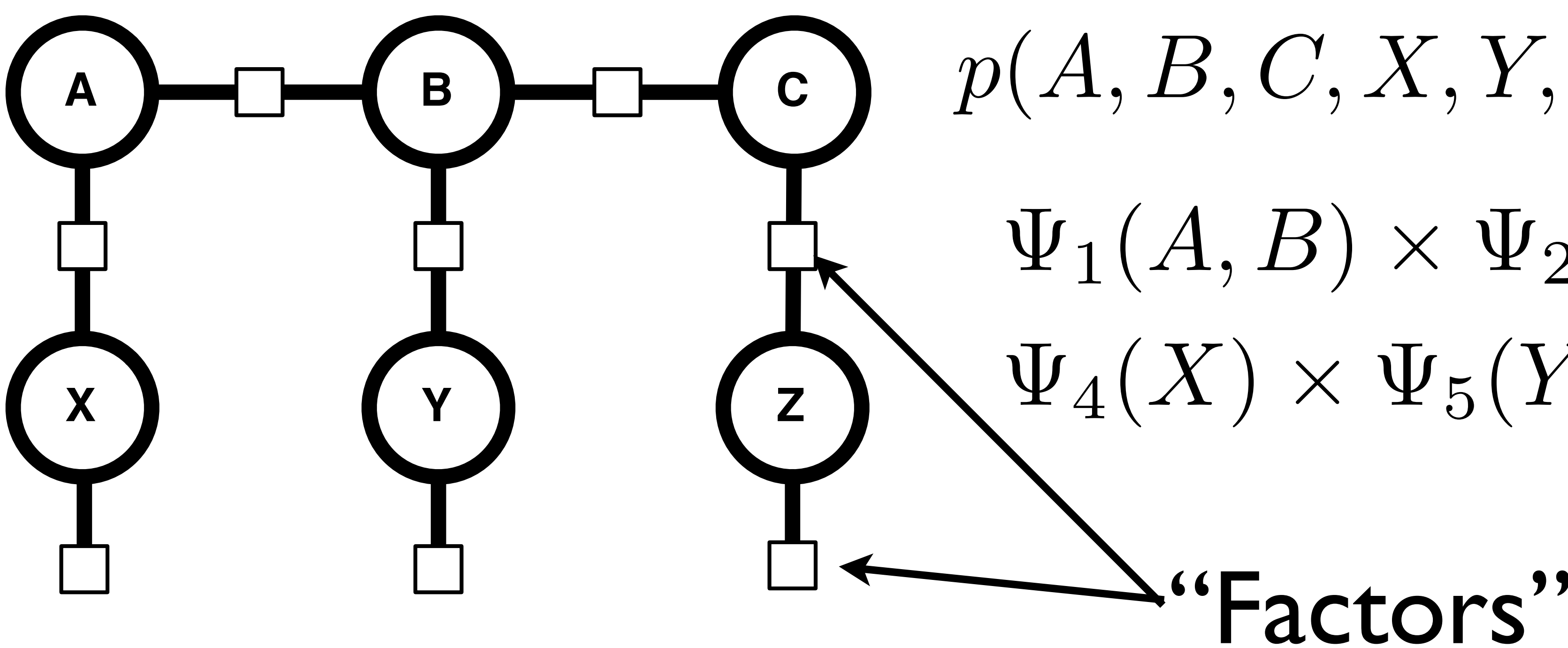

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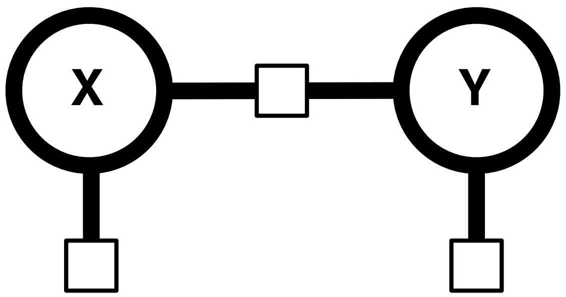
Computing Z



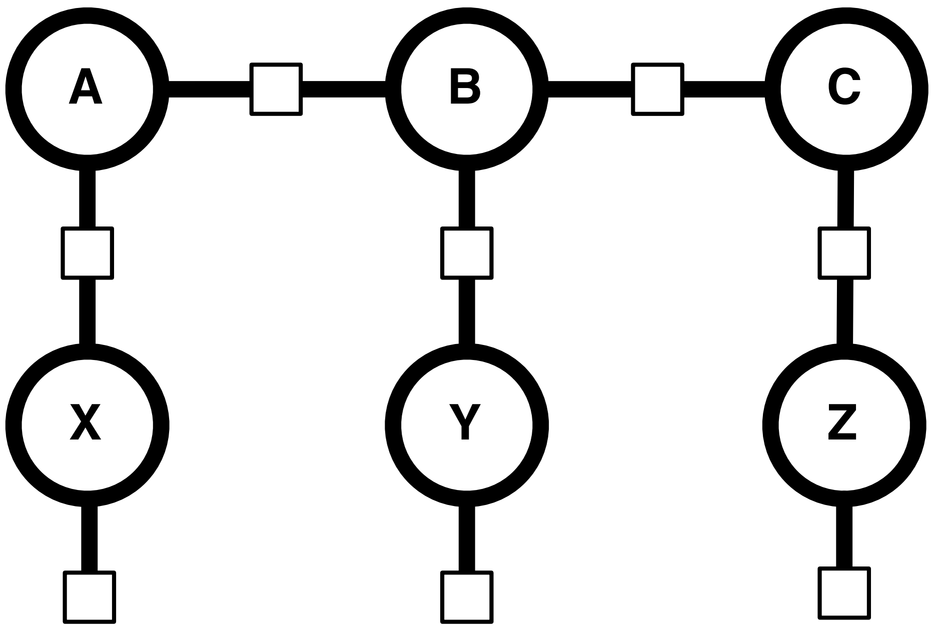
$$\mathcal{X} = \{\texttt{a}, \texttt{b}, \texttt{c}\}$$
$$X \in \mathcal{X}$$
$$Y \in \mathcal{X}$$

$$Z = \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{X}} \Psi_1(x, y)\Psi_2(x)\Psi_3(y)$$

When the graph has certain structures (e.g., chains), you can factor to get polytime DP algorithms.

$$Z = \sum_{x \in \mathcal{X}} \Psi_2(x) \sum_{y \in \mathcal{X}} \Psi_1(x, y)\Psi_3(y)$$

Log-linear models



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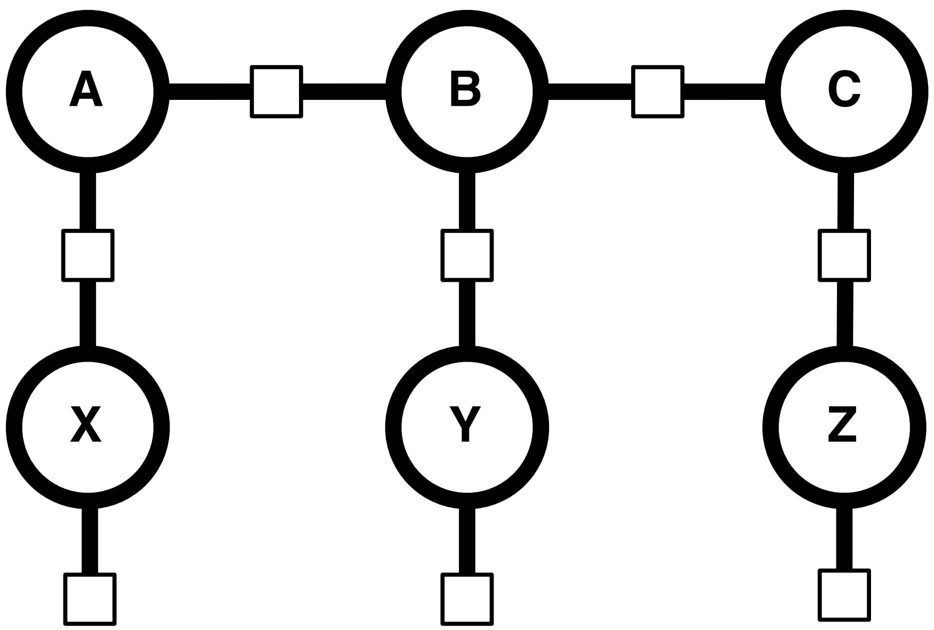

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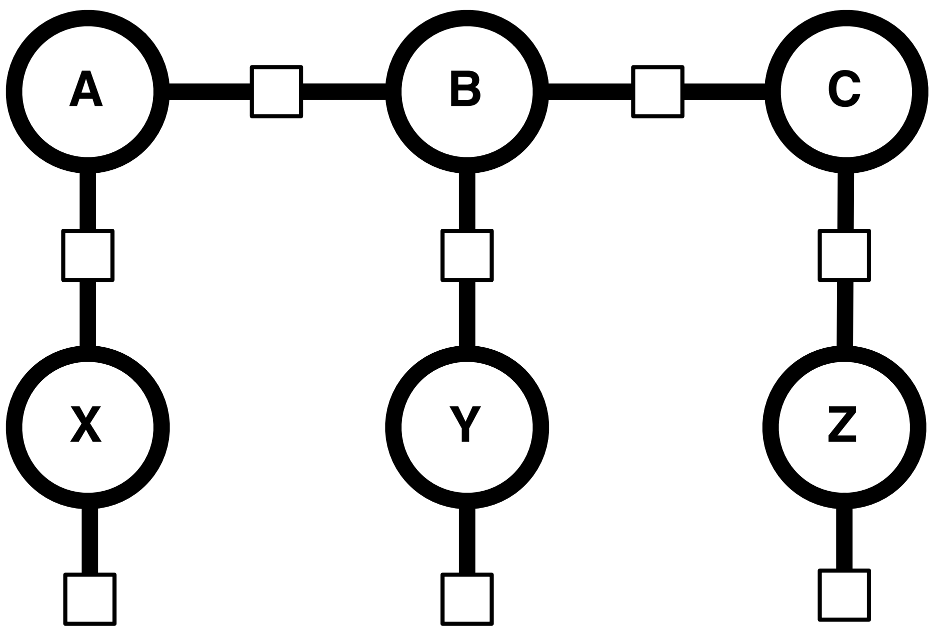

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Weights (learned)

Feature functions (specified)

Random Fields

- **Benefits**
  - Potential functions can be defined with respect to arbitrary features (functions) of the variables
  - Great way to incorporate knowledge
- **Drawbacks**
  - Likelihood involves computing Z
  - Maximizing likelihood usually requires computing Z (often over and over again!)

Conditional Random Fields

- Use MRFs to parameterize a conditional distribution. Very easy: let feature functions look at **anything** they want in the "input"

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$$p(\mathbf{y} \mid \mathbf{x}) = \frac{1}{Z_{\mathbf{w}}(\mathbf{y})} \exp \sum_{F \in \mathcal{G}} \sum_{k} w_k f_k(F, \mathbf{x})$$

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All factors in the graph of $\mathbf{y}$

Parameter Learning

- CRFs are trained to maximize conditional likelihood

$$\hat{\mathbf{w}}_{\text{MLE}} = \arg\max_{\mathbf{w}} \prod_{(\mathbf{x}_i, \mathbf{y}_i) \in \mathcal{D}} p(\mathbf{y}_i \mid \mathbf{x}_i \; ; \mathbf{w})$$

- Recall we want to directly model

$$p(\mathbf{a} \mid \mathbf{e}, \mathbf{f})$$

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Gold reference alignments!

CRF for Alignment

- One of many possibilities, due to Blunsom & Cohn (2006)

$$p(\mathbf{a} \mid \mathbf{e}, \mathbf{f}) = \frac{1}{Z_{\mathbf{w}}(\mathbf{e}, \mathbf{f})} \exp \sum_{i=1}^{|\mathbf{e}|} \sum_{k} w_k f(a_i, a_{i-1}, i, \mathbf{e}, \mathbf{f})$$

- a has the same form as in the lexical translation models (still make a one-to-many assumption)
- w_k are the model parameters
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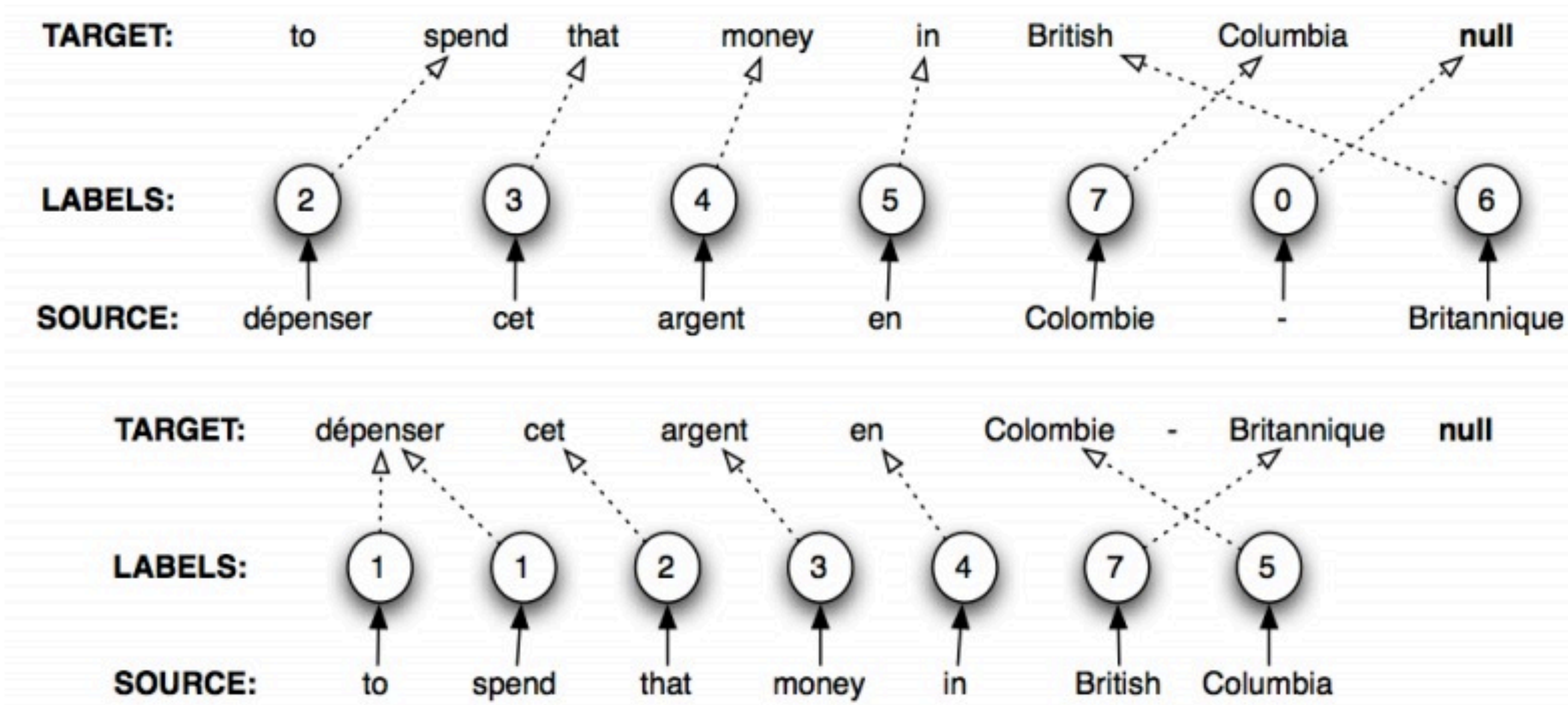
$$\boxed{O(n^2 m) \approx O(n^3)}$$

Model



- Labels (one per target word) index source sentence
- Train model (e,f) and (f,e) [inverting the reference alignments]

Experiments

Alignment Experiments:

- French - English (Canadian Hansards corpus NAACL '03)
- 484 word-aligned sentences (100 training, 37 devel. and 347 testing)
- 1.1M sentence-aligned sentences
- We present GIZA++ model 4 results for comparison

pervez musharrafs langer abschied

Identical word

pervez musharraf ’s long goodbye

Identical word

pervez **musharrafs** langer abschied

Matching prefix

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Lexical Features

- Word $\leftrightarrow$ word indicator features
- Various word $\leftrightarrow$ word co-occurrence scores
  - IBM Model 1 probabilities (t→s , s→t)
  - Geometric mean of Model 1 probabilities
  - Dice's coefficient [binned]
  - Products of the above

Lexical Features

- Word class ↔ word class indicator
  - **NN** translates as **NN** (`NN_NN=1`)
  - **NN** does not translate as **MD** (`NN_MD=1`)
- Identical word feature
  - **2010 = 2010** (`IdentWord=1 IdentNum=1`)
- Identical prefix feature
  - **Obama ~ Obamu** (`IdentPrefix=1`)
- Orthographic similarity measure [binned]
  - **Al-Qaeda ~ Al-Kaida** (`OrthoSim050_080=1`)

Other Features

- Compute features from large amounts of unlabeled text
  - Does the Model 4 alignment contain this alignment point?
  - What is the Model 1 posterior probability of this alignment point?

Results

Alignment Results:

	Precision	Recall	F-score
French $\rightarrow$ English	0.97	0.86	0.91
French $\leftarrow$ English	**0.98**	0.83	0.91
French $\leftrightarrow$ English	0.96	0.90	0.93
French $\rightarrow$ English (+ibm model4)	**0.98**	0.88	0.93
French $\leftarrow$ English (+ibm model4)	**0.98**	0.87	0.93
French $\leftrightarrow$ English (+ibm model4)	**0.98**	0.91	**0.95**
GIZA++ (French $\leftrightarrow$ English)	0.87	**0.95**	0.91

Summary

- CRFs provide an efficient model for word alignment that outperforms current models, even when only a small number of word aligned sentences are available
- A diverse range of features can be beneficial to word alignment performance, in particular Markov sequence features improve f-score
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Unfortunately, you need **gold alignments**!

Putting the pieces together

$$p(\mathbf{e})$$

$$p(\mathbf{e} \mid \mathbf{f}, m)$$

$$p(\mathbf{e}, \mathbf{a} \mid \mathbf{f}, m)$$

$$p(\mathbf{a} \mid \mathbf{e}, \mathbf{f})$$

Putting the pieces together

- We have seen how to model the following:

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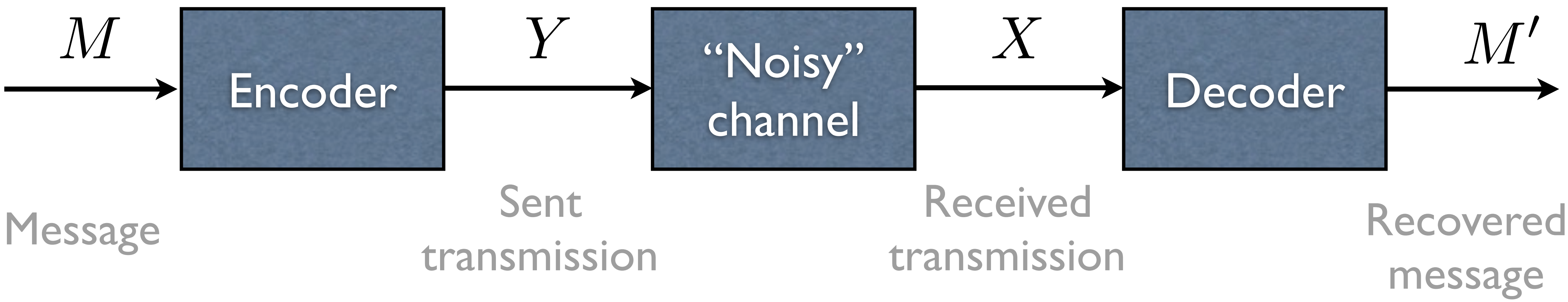
$$p(\mathbf{e}, \mathbf{a} \mid \mathbf{f}, m)$$

$$p(\mathbf{a} \mid \mathbf{e}, \mathbf{f})$$

- Goal: a better model of $p(\mathbf{e} \mid \mathbf{f}, m)$ that knows about $p(\mathbf{e})$

One naturally wonders if the problem of translation could conceivably be treated as a problem in cryptography. When I look at an article in Russian, I say: '***This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode.***'

Warren Weaver to Norbert Wiener, March, 1947



Claude Shannon. "A Mathematical Theory of Communication" 1948.

$$p(y) \quad p(x|y) \quad p(x)$$

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$$\boxed{p(y) \quad p(x|y)} \quad p(x)$$

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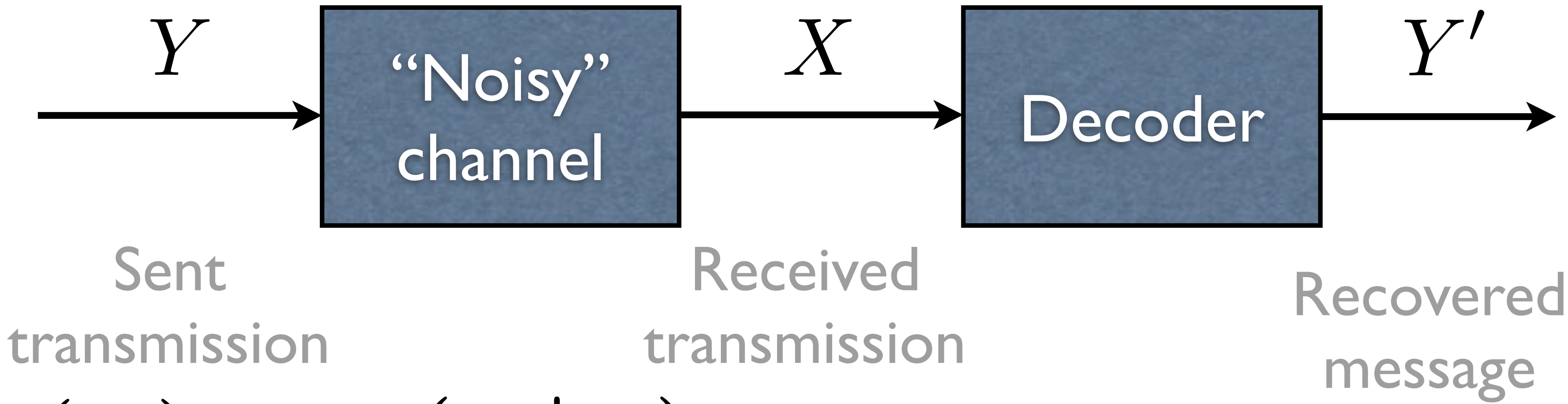
$$p(y) \quad p(x|y)$$

Shannon's theory tells us:

1) how much data you can send
2) the limits of compression
3) why your download is so slow
4) how to translate

Claude Shannon. "A Mathematical Theory of Communication" 1948.


Y
"Noisy" channel
X
Decoder
Y'
Sent transmission
Received transmission
Recovered message

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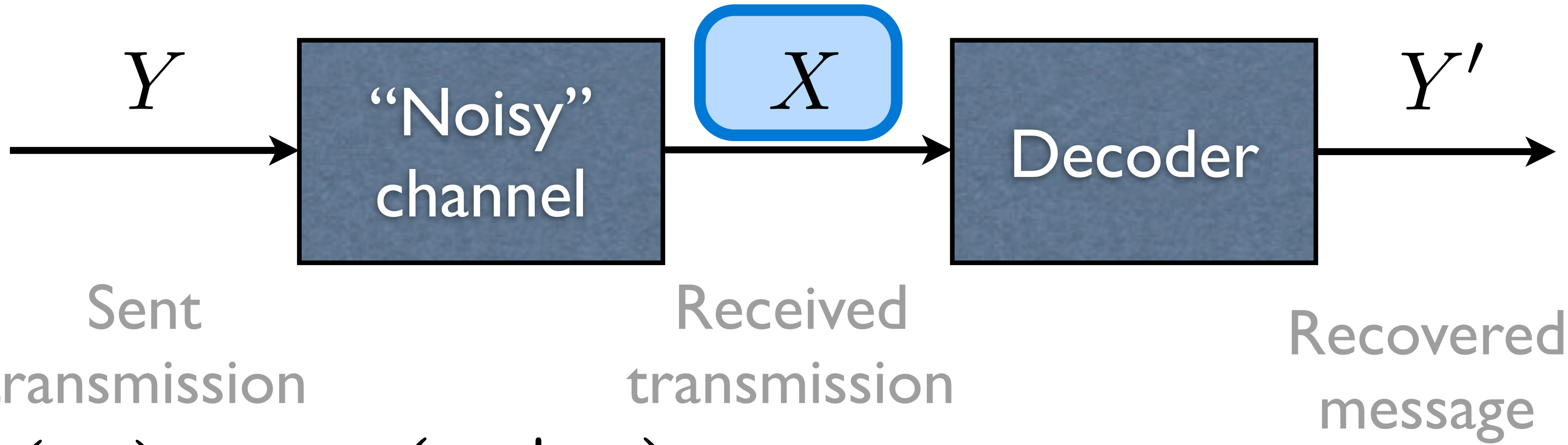

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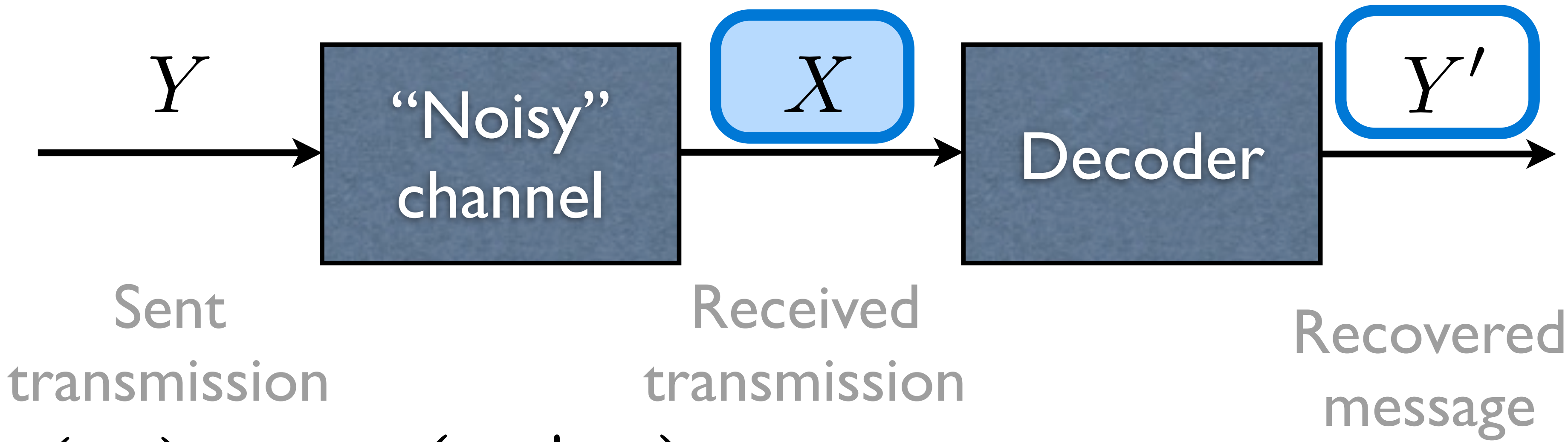
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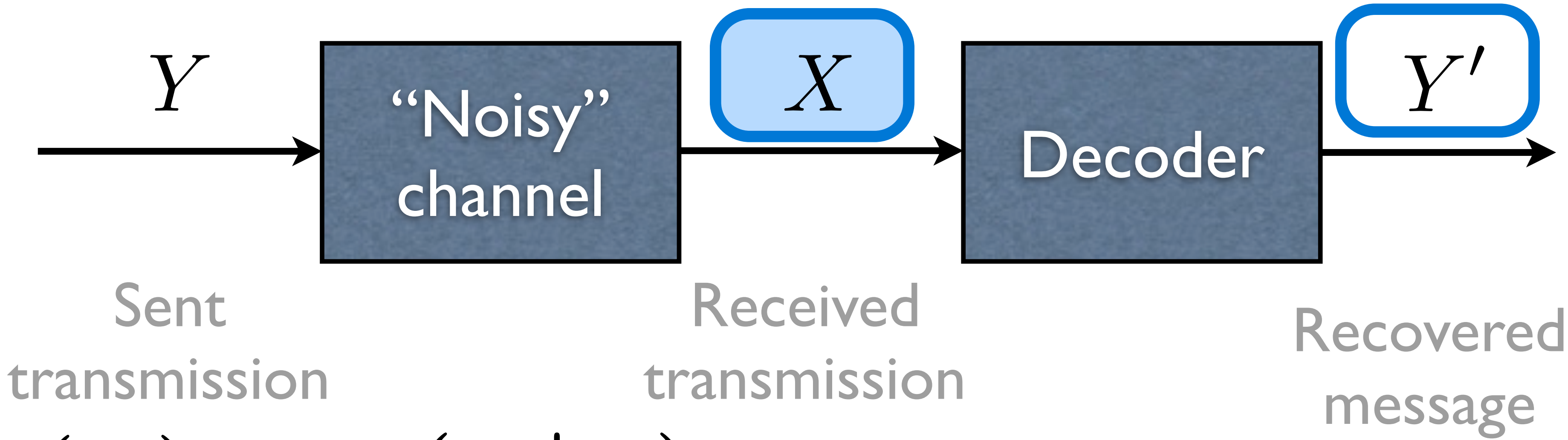

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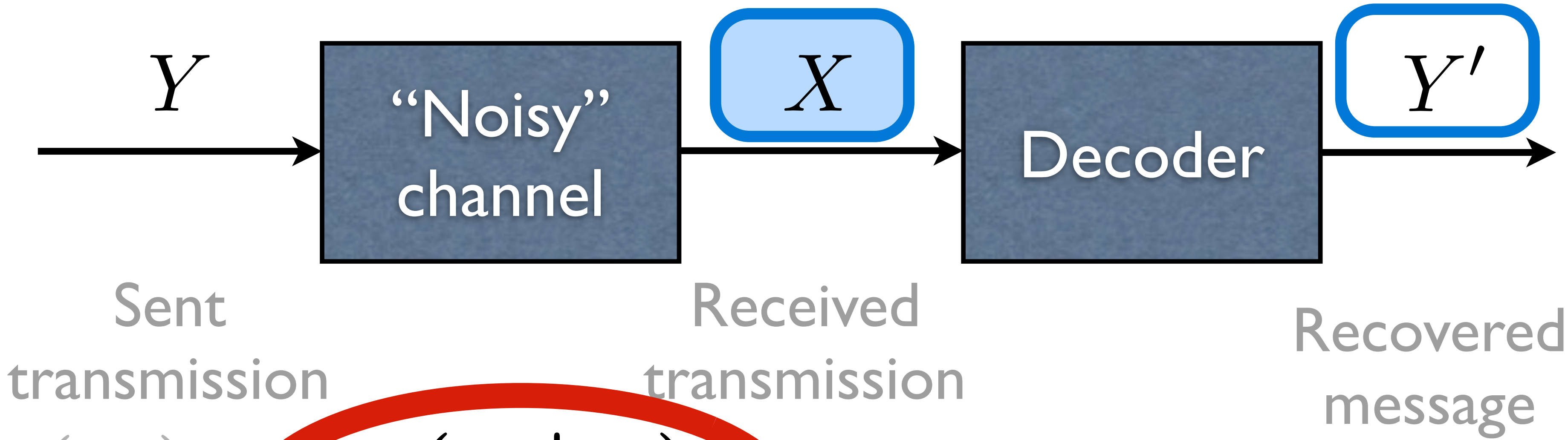


$$p(y)\,p(x|y) \not\propto$$

$$\boxed{y'} = \arg\max_y p(y|x)$$

Y → "Noisy" channel → X → Decoder → Y'

Sent transmission

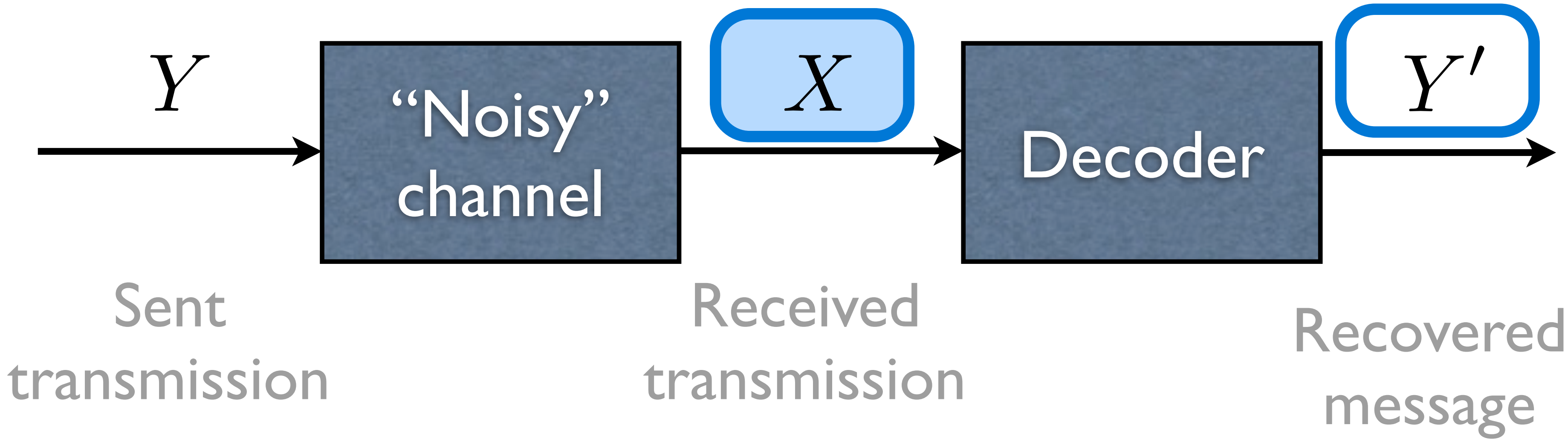
Received transmission

Recovered message

$p(y)$ $p(x|y)$

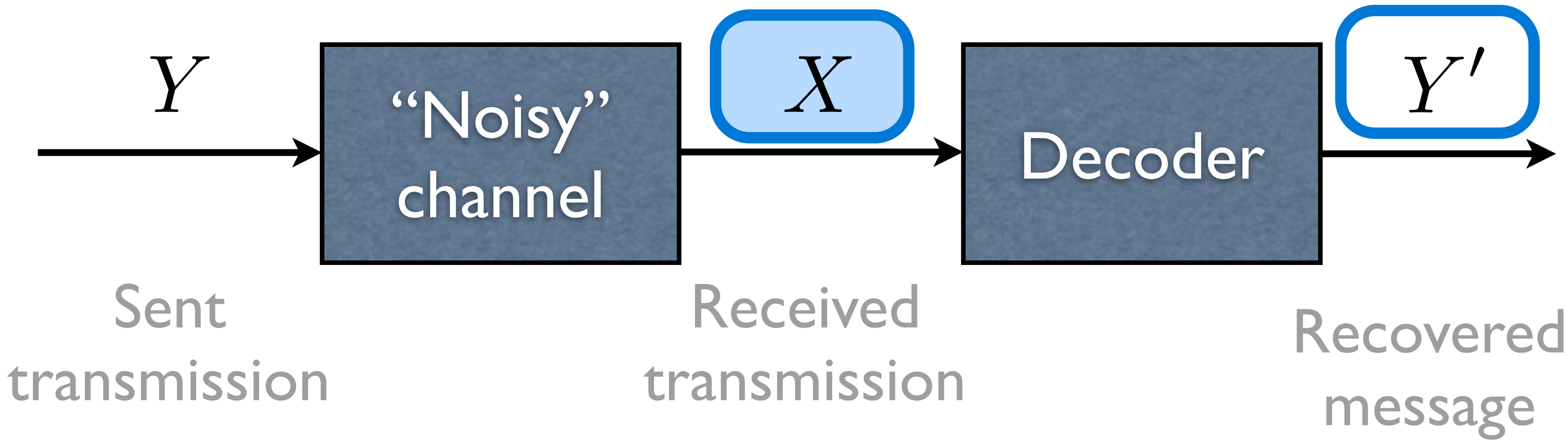
$$\boxed{y'} = \arg\max_{y} p(y|x)$$

I can help.



$$\boxed{y'} = \arg\max_y p(y|x)$$

$$= \arg\max_y \frac{p(x|y)p(y)}{p(x)}$$



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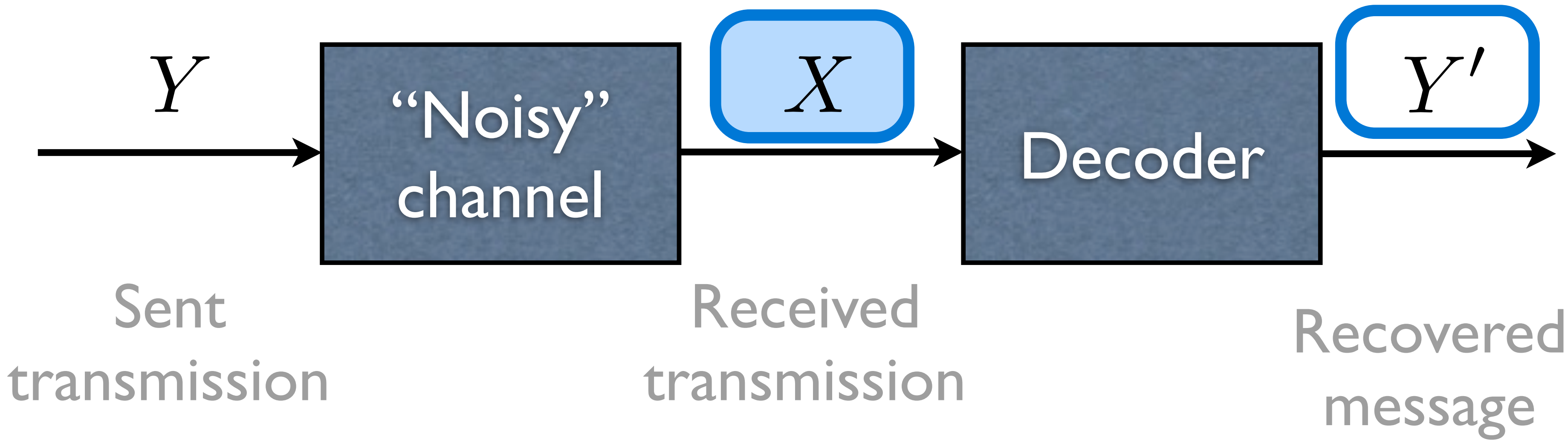
Denominator doesn't depend on y.



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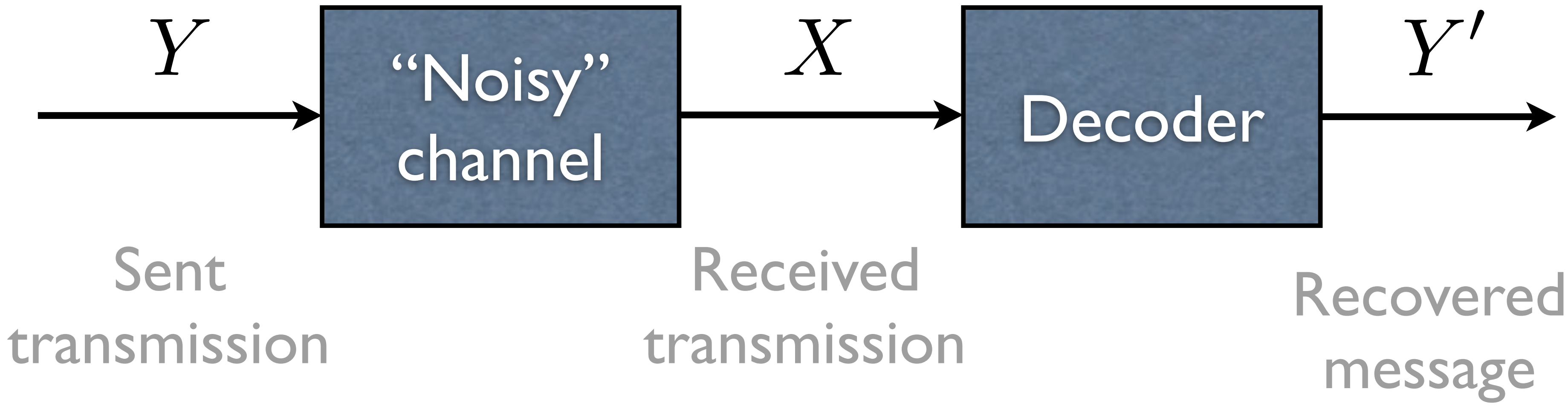

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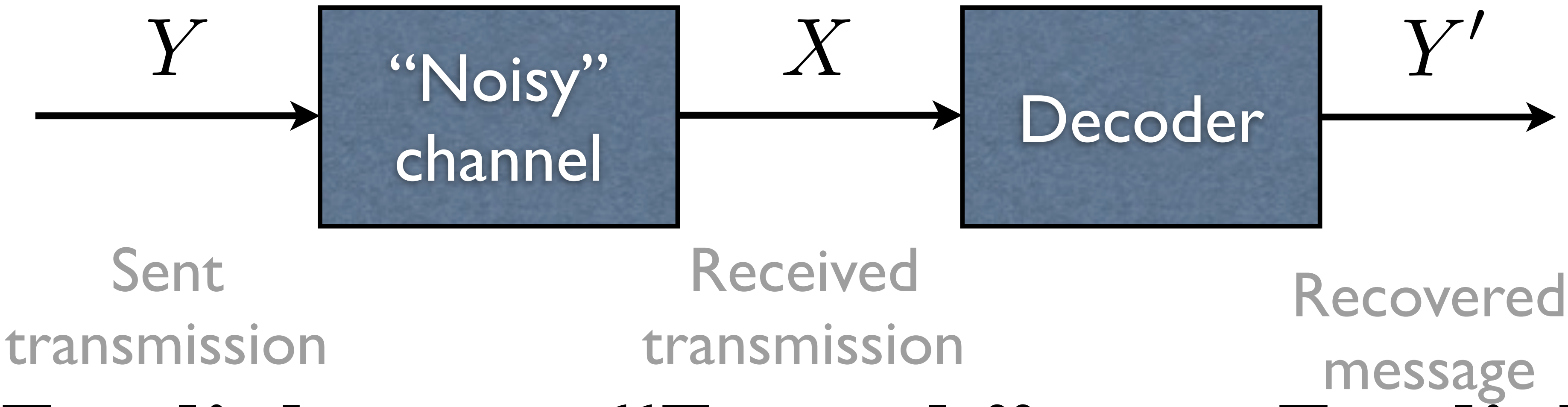

English **"French"** **English'**

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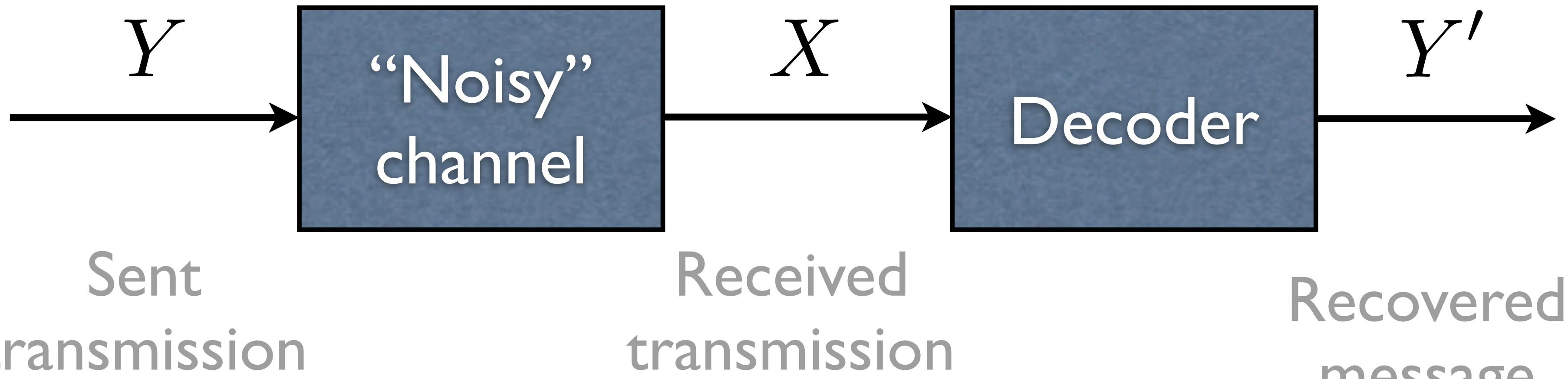

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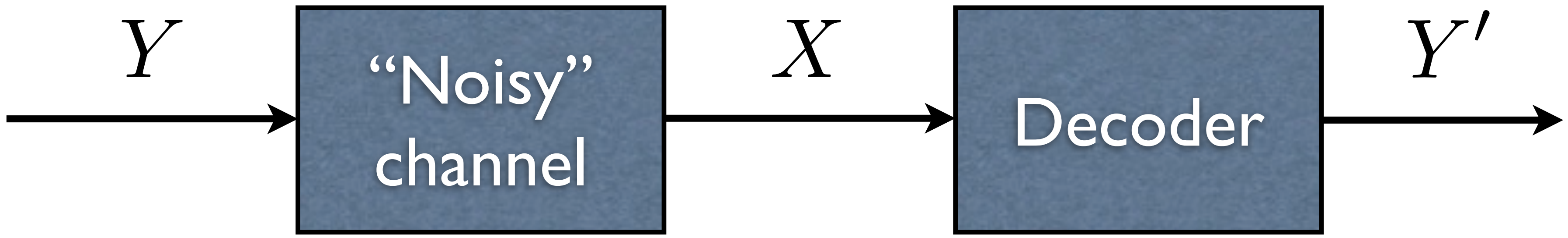
translation model



Sent transmission

English

Received transmission

"French"

Recovered message

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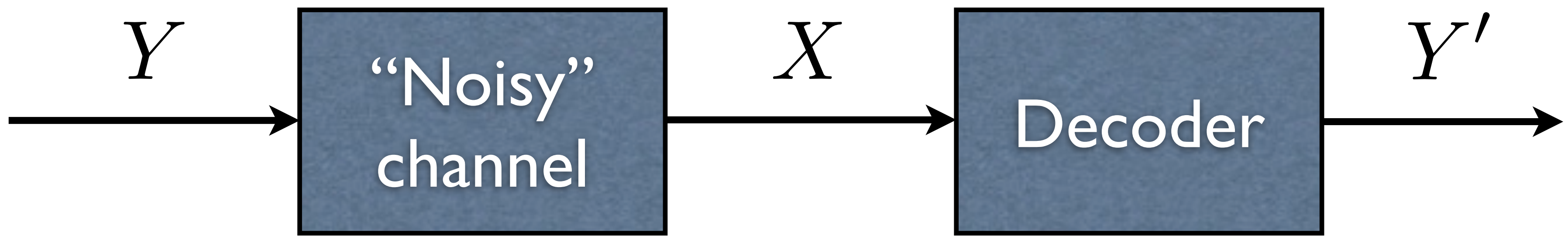
translation model

language model



Sent transmission

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translation model

language model

Other noisy channel applications: OCR, speech recognition, spelling correction...

Division of labor

- **Translation model**
  - probability of translation *back* into the source
  - ensures **adequacy** of translation
- **Language model**
  - is a translation hypothesis “good” English?
  - ensures **fluency** of translation

$p(\mathbf{e})$ English

$p(\mathbf{f} \mid \mathbf{e})$

$p(\mathbf{e})$ English $\longrightarrow$ Հայերէն

$p(\mathbf{f} \mid \mathbf{e})$

$p(\mathbf{e})$ English → Հայերէն

$$
\begin{aligned}
\mathbf{e}^* &= \arg\max_{\mathbf{e}} p(\mathbf{e} \mid \mathbf{f}) \\
&= \arg\max_{\mathbf{e}} p(\mathbf{f} \mid \mathbf{e}) \times p(\mathbf{e})
\end{aligned}
$$

Announcements

- Upcoming language-in-10
  - Tuesday: Jon/Austin - Русский
- Leaderboard is functional

		Assignments				
Rank	Handle	#0	#1 AER	#3 Spearman's	#2 model score	#4 BLEU
	oracle	8	0			
1	db	16	0.433932			
	baseline	10	0.434484			
2	zero	18	0.434484			
3	Victor	24	0.438705			
	default	9	0.788911			
4	HBH	10				