Universitat Politècnica de València
Master en Inteligencia Artificial, Renoconocimiento de Formas e Imagen Digital
Master in Artificial Intelligence, Pattern Recognition and Digital Imaging
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MACHINE TRANSLATION

1. Introduction to Machine Translation

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Translation and Machine Translation

Translation:
The process of translating words or text from one language into another [1].

Machine translation:
Translation carried out by a computer [1].

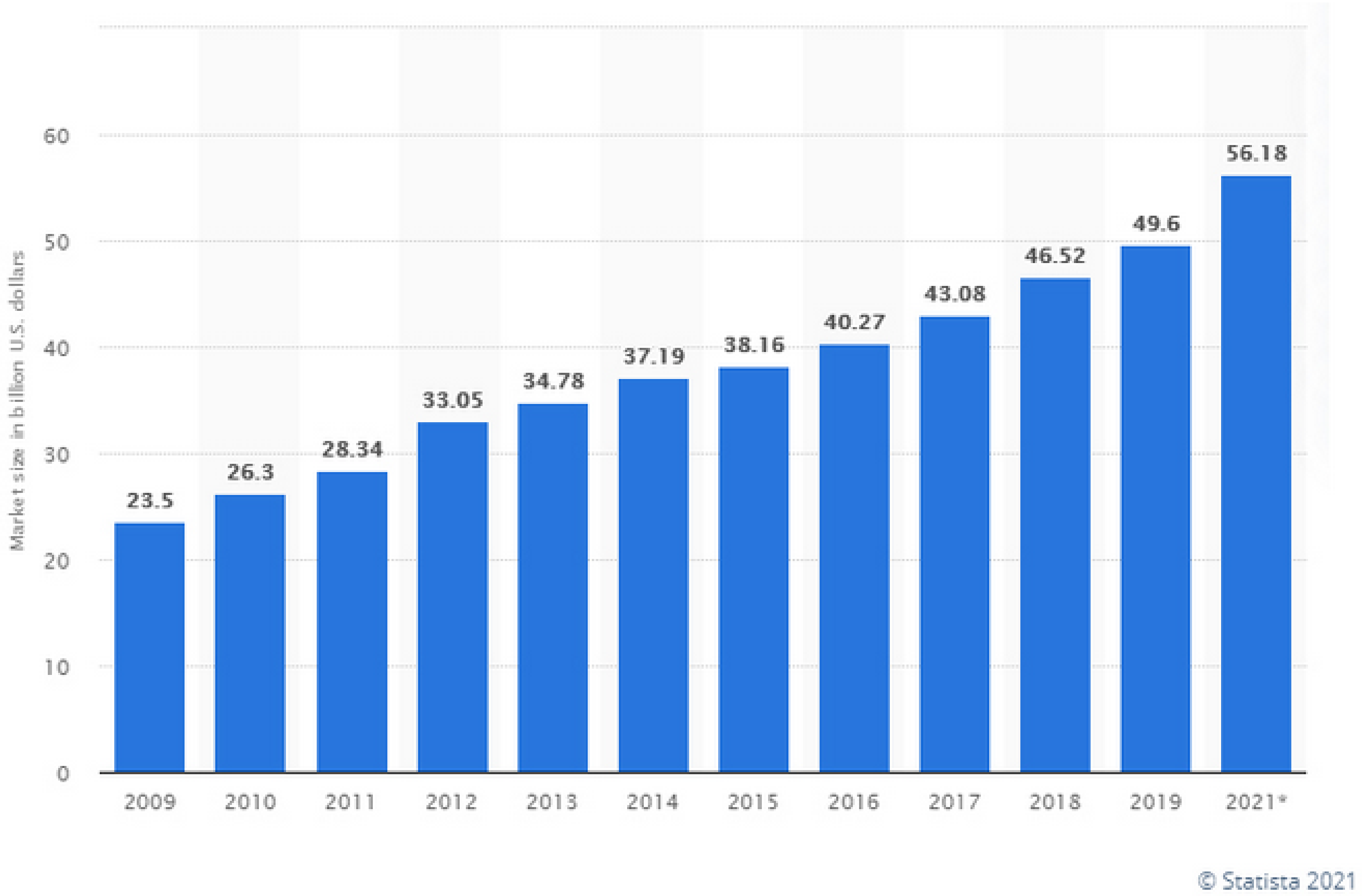
[1] English Oxford Dictionaries

Translation Industry Statistics[1]

- 7,139 languages being spoken today.
- Approximately 42% of languages are endangered.
- English is the most spoken language, while Mandarin Chinese has the most native speakers.
- The most widely used language on the internet is English, the second is Chinese, and third is Spanish at 8%.

[1] Lim 2022 Translation Industry Trends and Stats
https://redokun.com/blog/translation-statistics

Translation Industry Statistics[1]



[1] Lim 2022 Translation Industry Trends and Stats
https://redokun.com/blog/translation-statistics

Translation Industry Statistics[1]

- Europe at 49% of language services market, North America at 39.4%.
- The translation service market size grew by 40% during COVID-19.
- The machine translation market:
  - USD 650 million in 2020.
  - Expected to reach USD 3 billion by 2027.
- Increasing of demand in healthcare, medical industries, social networking, ...

[1] Lim 2022 Translation Industry Trends and Stats
https://redokun.com/blog/translation-statistics

Translation Industry Statistics[1]

- 640,000 human translators worldwide,
- 88% of full-time professional translators use at least 1 CAT tool.
- Translators estimate that using translation software can boost their productivity by at least 30%.
- The percentage of projects for end-clients using machine translations climbed from 13% in 2019 to 24% in 2020.

[1] Lim 2022 Translation Industry Trends and Stats
https://redokun.com/blog/translation-statistics

MT objectives: Facts

- MT is useful.
- There are many situations that MT systems produce reliable, if less than perfect, translations at high speed. In some circumstances, MT systems can produce good quality outputs.

  The first book translated by a MT system to French (12/9/2018): “Deep Learning” by Goodfellow, Bengio & Courville.

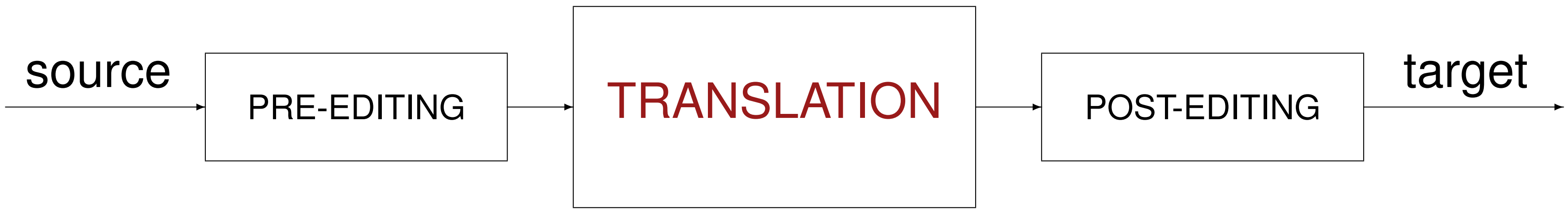
  https://www.usinenouvelle.com/editorial/le-premier-livre-traduit-par-une-ia-est-un-manuel-de-deep-learning.N740664

- Human parity and Super-Human Performance in MT [Toral 2020]
  `https://www.youtube.com/watch?v=wMhyEiZUCY4&t=1404s` (From 15:45 min)
- MT does not threaten translators’ jobs: High demand of translations and too repetitive translation jobs.
- Speech-to-speech MT is still a research topic, but ...
- There are many open research problems in MT.

Need of pre/post-editing

- While the number of errors and bad constructions is high, “post-editing” can make the result useful.

- Many problems could have been avoided by making the source text “simpler”.



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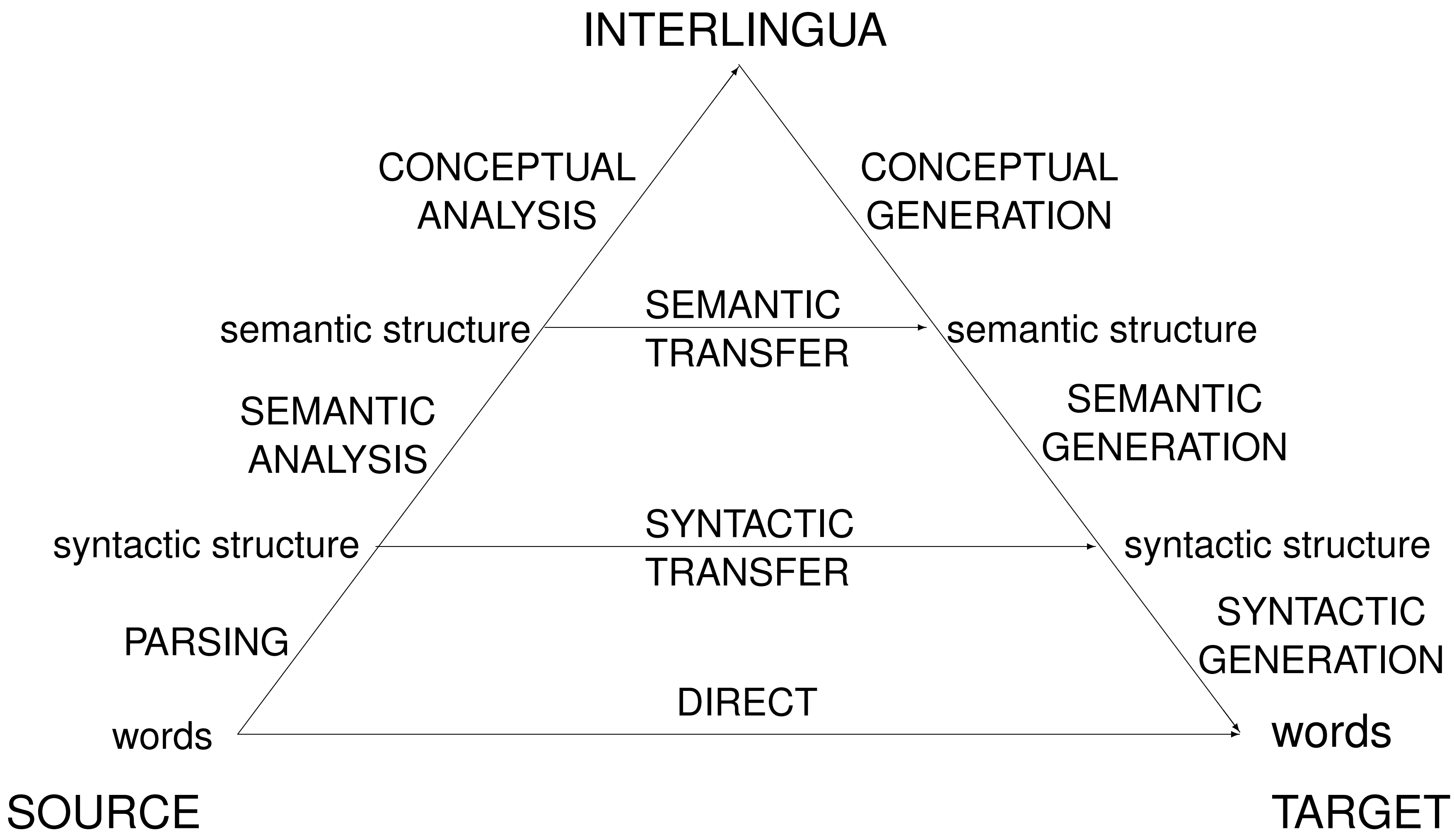
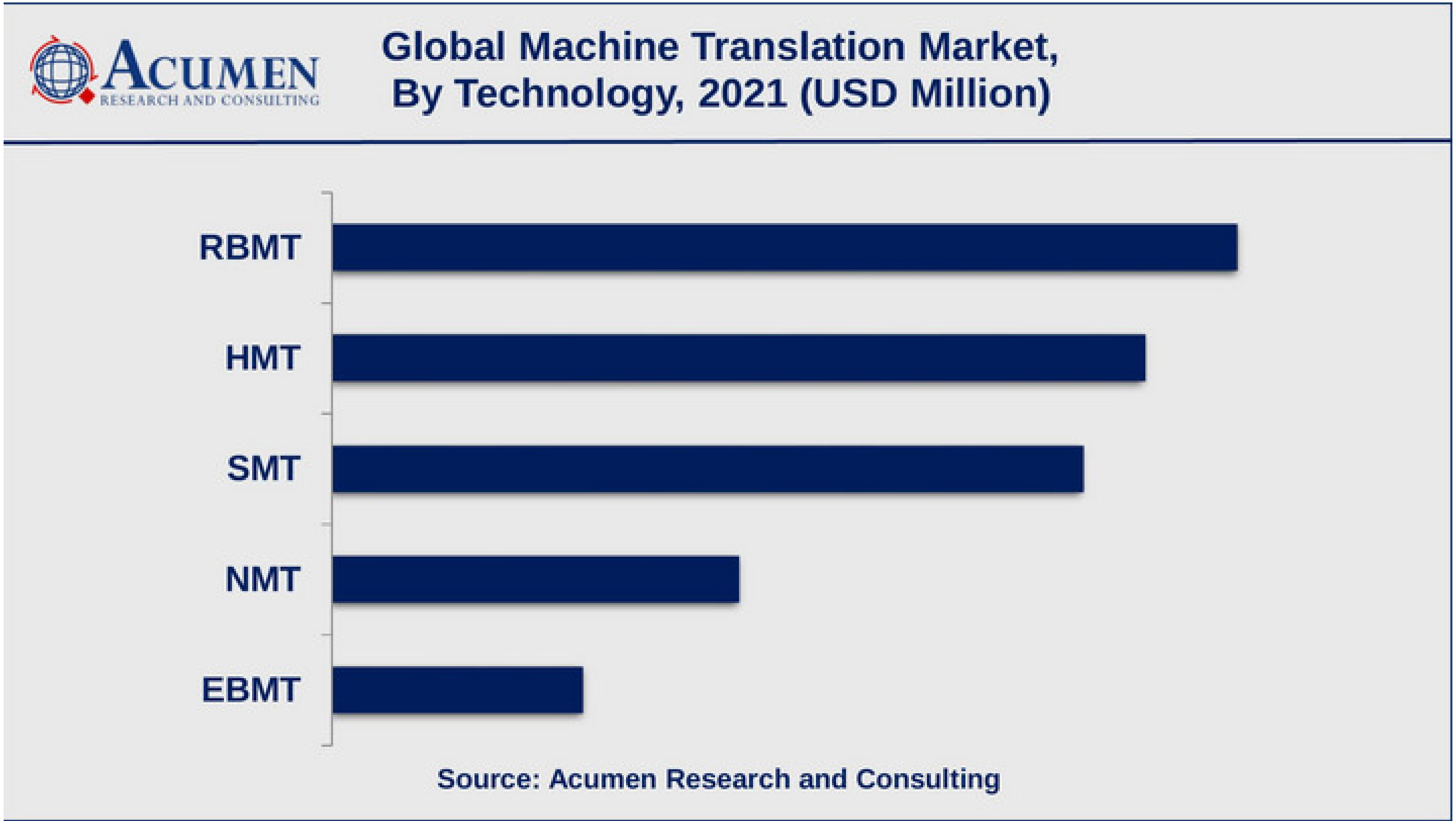
Approaches to MT: Vauquois triangle



Approaches to MT: Technologies

- (Linguistic) knowledge-based methods
- (Memorized) example-based methods
  - Translation memories
- Statistical models
  - Alignment models
  - Finite-state models
  - **(Deep) Neural networks**
- Hybrid models

Approaches to MT: Technologies



Approaches to MT: Technologies[1]

- Neural MT is more expensive to train than statistical MT, but the quality improvement is well worth any cost difference. Many systems are deprecating their older statistical models in favor of neural learning.
- The language pairs you need: Statistical MT is often sufficient for certain language pairs such as Latin-based languages with similar grammatical rules and syntax.
- The amount of data you have: Neural MT requires the processing of large quantities of text for it to learn and for you to reap the benefits.
- Customer-facing content, like marketing or sales materials that reflect brand quality, requires the combination of machine translation and experienced human translators doing post-editing. Internal documentation may be able to be achieved by using basic machine translation when time and cost are factors.

[1] Machine Translation: What It Is, and How It Works. 2023.

https://phrase.com/blog/posts/machine-translation/#which-machine-translation-type-should-i-use

Assessment

- Manual from test sentences:
  - Human evaluation (expensive)
- Automatic from test sentences with reference translation:
  - Editing Distances:**Translation Error Rate (TER)**
  - Multi-reference TWER.
  - N-gram based: **BLEU** and NIST scores.
  - Meteor
  - **Beer**
  - ...
- Automatic from test sentences with reference translation for CAT:
  - Word-Stroke Ratio (WSR).
  - Key-stroke ratio (KSR).
  - Mouse Action Ratio (MAR)
  - ...

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Brief history of MT

- **1949** Weaver: Information-theory based approach.
- **1957** Chomsky: Natural language is not governed by statistics.
- **1960** ALPAC (Automatic Language Processing Advisory Committee) report: No useful MT results are foreseen.
- **1960-2000**
  - SYSTRAN system: based on dictionaries.
  - Several (linguistic) knowledge-based approaches.
- **1989-95** "Empiricists" methods are introduced: corpus-based and statistical approaches (IBM, 1989)
- **1995-nowadays** "Empiricists" methods are thriving. Speech-to-speech MT in limited domains.

Recent history of MT: “Empiricists” methods

- **1989-1995** Statistical approach to MT by IBM Yorktown Heights researchers:
  - Hansards Parallel English/French transcriptions of parliamentary discussions.
  - DARPA competitive assessment (1994): Results comparable to those achieved by traditional approaches.
- **1995-2010** Development of statistical techniques and other empiricists methods:
  - Great progress on the statistical approach.
  - Other empiricist techniques: Memory-based, finite-state, etc.
  - Computer assisted translation.
- **2010-2015** Practical use of statistical machine translation and a new approach:
  - Industrial use of Moses.
  - **Continuous space representation: Neural machine translation**.
  - Adaptation, online learning, multimodal, multilingual, data filtering, ...
  - Advanced computer assisted translation: interactive, multimodal, adaptative, ...
- **2016-** Practical use of neural machine translation:
  - Industrial use of NMT.
  - New neural models: Transformer.
  - Topics: learning from monolingual corpora, low-resource languages, pre-trained models for NLP, prompting, ...

Machine translation systems

- Text translation systems
  - GoogleTrans: http://www.google.com/language_tools
  - DeepL: https://www.deepl.com/en/translator
  - SYSTRAN: https://www.systran.net/en/translate/
  - Microsoft Translator: https://www.bing.com/translator
  - Amazon Translate: https://aws.amazon.com/es/getting-started/hands-translate-text-between-languages-cloud/

  - SisHiTra: https://demosmt.prhlt.upv.es/sishitra/
  - Apertium: http://www.apertium.org/

Machine translation systems

- Computer assisted (aided) translation systems
  - TRANSTYPE:
    `http://rali.iro.umontreal.ca/rali/?q=en/node/1282`
  - Déjàvu:
    `http://www.atril.com/`
  - TRADOS:
    `https://www.sdltrados.com/products/`
  - CasMaCat:
    `https://demosmt.prhlt.upv.es/matecat-test/translate/demo-eutt2.xliff/es/1-fmttqpvc/demo@4002#1`
  - Neural Machine Translation
    `https://demosmt.prhlt.upv.es/inmt/`

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General Framework

- Every sentence y from a *target* language is considered as a possible translation of a given sentence x from a *source* language.

- For each possible pair of sentences y, x, there is a probability $\Pr(y \mid x)$.

- $\Pr(y \mid x)$ should be *low* for pairs (y, x) such as:

  (una habitación con vistas al mar , are all expenses included in the bill ?)

- $\Pr(y \mid x)$ should be *high* for pairs such as:

  (¿ hay alguna habitación tranquila libre ? , is there a quiet room available ?)

- Goal of statistical machine translation: given a source sentence x search for a target sentence $\hat{y}$ such that (Risk minimization):

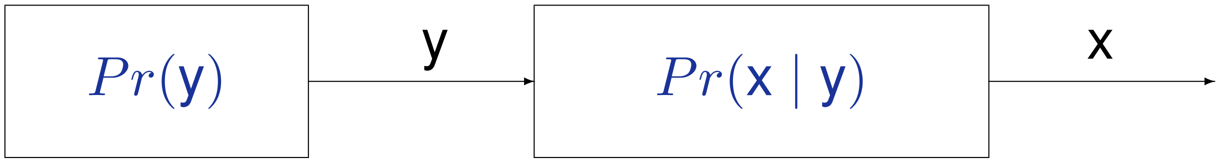
$$\hat{y} = \underset{y}{\operatorname{argmax}} \Pr(y \mid x)$$

An inverse (generative) approach

Decompose $\Pr(\mathsf{y} \mid \mathsf{x})$ using Bayes' rule:

$$\hat{\mathsf{y}} = \underset{\mathsf{y}}{\operatorname{argmax}} \Pr(\mathsf{y} \mid \mathsf{x}) = \underset{\mathsf{y}}{\operatorname{argmax}} \frac{\Pr(\mathsf{x} \mid \mathsf{y}) \cdot \Pr(\mathsf{y})}{\Pr(\mathsf{x})} = \underset{\mathsf{y}}{\operatorname{argmax}} \Pr(\mathsf{x} \mid \mathsf{y}) \cdot \Pr(\mathsf{y})$$

A "distorted (noisy) channel model"



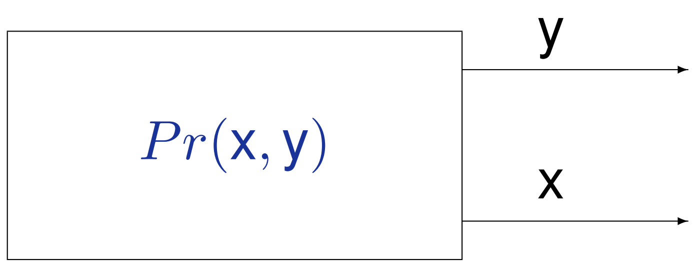
***Need:** a target-language model + alignment and lexicon models*

A generative (finite-state) approach

The direct probability can be decomposed in a different way:

$$\hat{y} = \underset{y}{\text{argmax}} \Pr(y \mid x) = \underset{y}{\text{argmax}} \frac{\Pr(x, y)}{\Pr(x)} = \underset{y}{\text{argmax}} \Pr(x, y)$$

A "joint" model



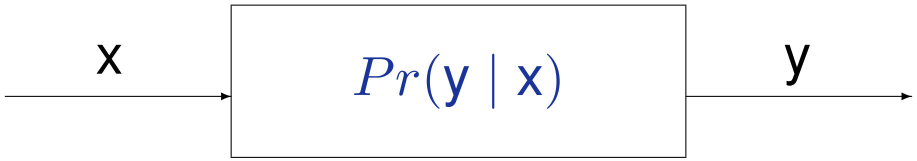
A stochastic finite-state transducer can model the joint distribution

A direct (discriminative) approach

Search for a target sentence with maximum *posterior* probability:

$$\hat{y} = \underset{y}{\text{argmax}} \, \mathrm{Pr}(y \mid x)$$

A “direct model”



Log-linear combination of models

Encoding-Decoding models

Log-linear combination of models

Search for a target sentence with maximum *posterior* probability:

$$\hat{\mathsf{y}} = \underset{\mathsf{y}}{\text{argmax}} \Pr(\mathsf{y} \mid \mathsf{x})$$

$$\hat{\mathsf{y}} = \underset{\mathsf{y}}{\text{argmax}} \frac{\exp\left(\sum_{k=1}^{K} \lambda_k h_k(\mathsf{x}, \mathsf{y})\right)}{\sum_{\mathsf{y}'} \exp\left(\sum_{k=1}^{K} \lambda_k h_k(\mathsf{x}, \mathsf{y}')\right)} = \underset{\mathsf{y}}{\text{argmax}} \sum_{k=1}^{K} \lambda_k h_k(\mathsf{x}, \mathsf{y})$$

- $h_1(\mathsf{x}, \mathsf{y}) = \log Pr(\mathsf{y})$, a language model
- $h_2(\mathsf{x}, \mathsf{y}) = \log Pr(\mathsf{y} \mid \mathsf{x})$, a translation model model
- $h_3(\mathsf{x}, \mathsf{y}) = \log Pr(\mathsf{x} \mid \mathsf{y})$, an inverse translation model model
- $\ldots$

Encoder-decoder models

Search for a target sentence with maximum *posterior* probability:

$$\hat{y} = \underset{y}{\text{argmax}} \Pr(y \mid x)$$

$$\hat{y} = \underset{y}{\text{argmax}} \prod_{i=1}^{I} P(y_i \mid y_1^{i-1}, a(x))$$

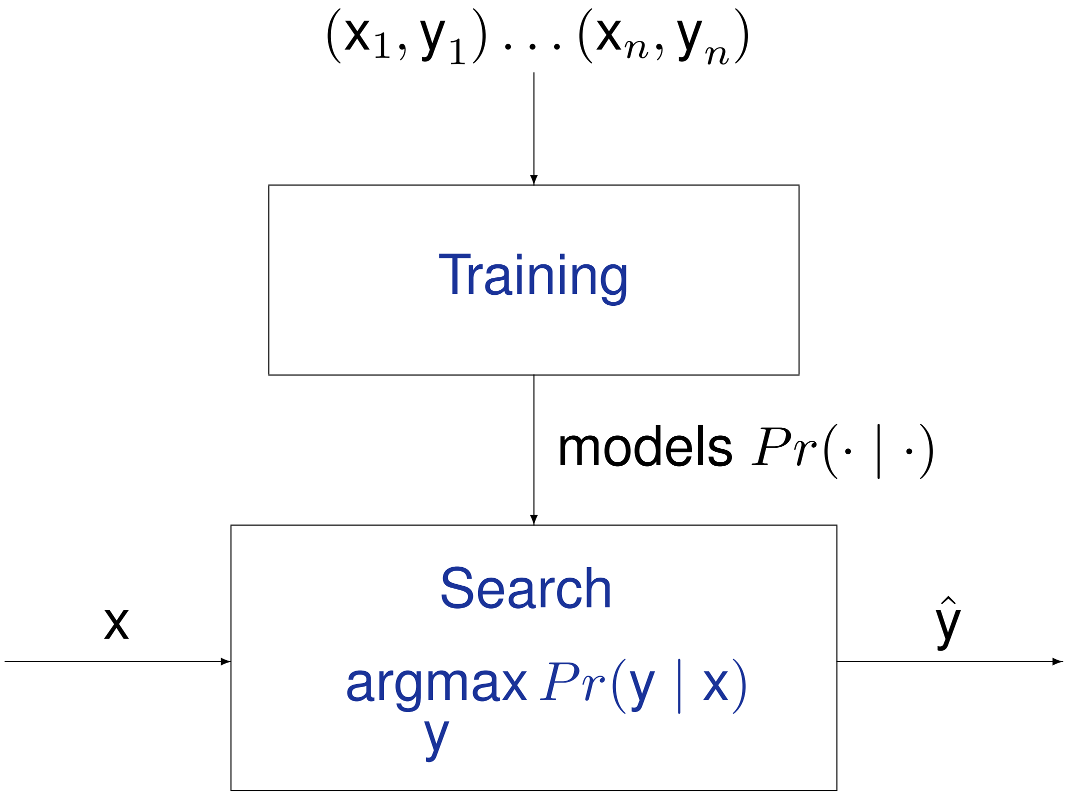
- Recurrent neuronal networks with an attention model.
- Full attention non-recurrent model: Transformer.
- A convolutional neuronal network.

Training and search

Search

$$\mathsf{x} \longrightarrow \boxed{\operatorname*{argmax}_{\mathsf{y}} Pr(\mathsf{y} \mid \mathsf{x})} \longrightarrow \hat{\mathsf{y}}$$

Training and search



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Speech-input translation

Given an input acoustic sequence v, search for a target sentence with maximum posterior probability:

$$\hat{\mathsf{y}} = \operatorname*{argmax}_{\mathsf{y}} \Pr(\mathsf{y} \mid \mathsf{v})$$

But this can be seen as a *"two-step process"*:

$$\mathsf{v} \longrightarrow \mathsf{x} \longrightarrow \mathsf{y}$$

where the *"hidden variable"* x accounts for all possible input decodings of v:

$$\hat{\mathsf{y}} \;=\; \operatorname*{argmax}_{\mathsf{y}} \sum_{\mathsf{x}} \Pr(\mathsf{y}, \mathsf{x} \mid \mathsf{v}) \;=\; \operatorname*{argmax}_{\mathsf{y}} \sum_{\mathsf{x}} \Pr(\mathsf{x}, \mathsf{y}) \cdot \Pr(\mathsf{v} \mid \mathsf{x})$$

(with the assumption: $\Pr(\mathsf{v} \mid \mathsf{x}, \mathsf{y})$ does not depend on the target sentence y)

Speech-input translation: Integrated approaches

$$\underset{\mathsf{y}}{\text{argmax}}\,\Pr(\mathsf{y} \mid \mathsf{v}) \quad \approx \quad \underset{\mathsf{y}}{\text{argmax}}\,\underset{\mathsf{x}}{\max}\,(\Pr(\mathsf{x},\mathsf{y}) \cdot \Pr(\mathsf{v} \mid \mathsf{x}))$$

- $\Pr(\mathsf{v} \mid \mathsf{x}) \approx$ ACOUSTIC MODELS
- $\Pr(\mathsf{x}, \mathsf{y}) \approx$ STOCHASTIC FINITE-STATE TRANSDUCERS

$$\underset{\mathsf{y}}{\text{argmax}}\,\Pr(\mathsf{y} \mid \mathsf{v}) \quad \approx \quad \underset{\mathsf{y}}{\text{argmax}} \prod_{i=1}^{I} P(y_i \mid y_1^{i-1}, a(\mathsf{v}))$$

- ENCODER-DECODER MODELS

Speech-input translation: A serial approach

$$\operatorname*{argmax}_{y} \max_{x} \left(\Pr(x, y) \cdot \Pr(v \mid x)\right) \quad = \quad \operatorname*{argmax}_{y} \max_{x} \left(\Pr(y \mid x) \cdot \Pr(x) \cdot \Pr(v \mid x)\right)$$

$$\boxed{\begin{array}{llll} 1. & \widehat{x} & \approx & \operatorname*{argmax}_{x} \Pr(x) \cdot \Pr(v \mid x) = \operatorname*{argmax}_{x} \Pr(x \mid v) \\ 2. & \widehat{y} & \approx & \operatorname*{argmax}_{y} \Pr(y \mid \widehat{x}) \end{array}}$$

- $\Pr(v \mid x) \approx$ ACOUSTIC MODELS
- $\Pr(y \mid x) \approx$ TRANSLATION MODELS
- $\Pr(x) \approx$ SOURCE LANGUAGE MODELS

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Text prediction for Interactive Machine Translation in CAT

Given a source text x and a "correct" *prefix* y_p of the target text, search for a *suffix* $\hat{\mathsf{y}}_s$, that maximizes the posterior probability over all possible sufixes:

$$\hat{\mathsf{y}}_s = \underset{\mathsf{y}_s}{\operatorname{argmax}} \Pr(\mathsf{y}_s \mid \mathsf{x}, \mathsf{y}_p)$$

Taking into account that $\Pr(\mathsf{x}, \mathsf{y}_p)$ does not depend on y_s, we can write:

$$\begin{aligned}\hat{\mathsf{y}}_s &= \underset{\mathsf{y}_s}{\operatorname{argmax}} \frac{\Pr(\mathsf{y}_p, \mathsf{y}_s \mid \mathsf{x})}{\Pr(\mathsf{y}_p \mid \mathsf{x})} \\ &= \underset{\mathsf{y}_s}{\operatorname{argmax}} \Pr(\mathsf{y}_p \mathsf{y}_s \mid \mathsf{x})\end{aligned}$$

Main difference with text-input machine translation: search over the set of suffixes.

Extension: Fix all correct segments,

Target language dictation in CAT

A *human* translator *dictates* the translation of a source text, x, producing a *target language* acoustic sequence v.

Given v and x, the system should search for a most likely decoding of v:

$$\hat{y} = \underset{y}{\operatorname{argmax}} \Pr(y \mid x, v)$$

By the assumption that $\Pr(v \mid x, y)$ does not depend on x,

$$\hat{y} = \underset{y}{\operatorname{argmax}} \Pr(v \mid y) \cdot \Pr(x \mid y) \cdot \Pr(y)$$

- $\Pr(v \mid y) \approx$ (TARGET LANGUAGE) ACOUSTIC MODELS
- $\Pr(x \mid y) \approx$ TRANSLATION MODEL
- $\Pr(y) \approx$ TARGET LANGUAGE MODEL

Similar to plain speech decoding, where: $\hat{y} = \underset{y}{\operatorname{argmax}} \Pr(v \mid y) \cdot \Pr(y)$

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Notation and basic concepts

- x and y will generally denote source and target texts, respectively
- Unconditional probabilities: $\Pr(Y = y) \equiv \Pr(y)$
- Conditional probabilities: $\Pr(Y = y \mid X = x) \equiv \Pr(y \mid x)$
- Joint probability: $\Pr(x, y) = \Pr(x) \cdot \Pr(y \mid x)$
- Bayes' rule: $\Pr(x \mid y) \cdot \Pr(y) = \Pr(y \mid x) \cdot \Pr(x)$
- Chain rule: $\Pr(x_1^I) = \Pr(x_1) \cdot \Pr(x_2 \mid x_1) \cdots \Pr(x_I \mid x_1^{I-1})$
- Marginal distribution: $\Pr(x) = \sum_{\forall y} \Pr(x, y)$
- Maximum aproximation: $\sum_{x \in A} \Pr(x) \approx \max_{x \in A} \Pr(x)$
- Expected values $\quad E_P(f(x)) \equiv E_x(f(x)) = \sum_x f(x)\, P(x)$

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