Imitation Attacks and Defenses for Black-box Machine Translation Systems

Eric Wallace, Mitchell Stern, Dawn Song

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Dawn Song

Production NLP Models Are Lucrative

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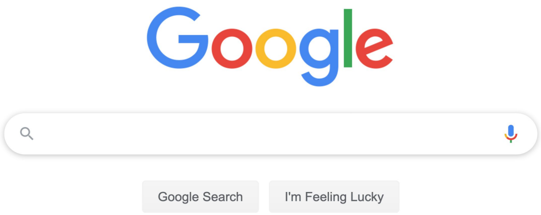
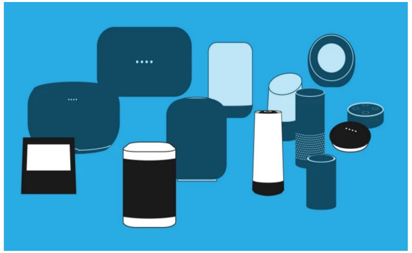


Information Retrieval

Machine Translation

Text + Speech Generation



Smart Assistants

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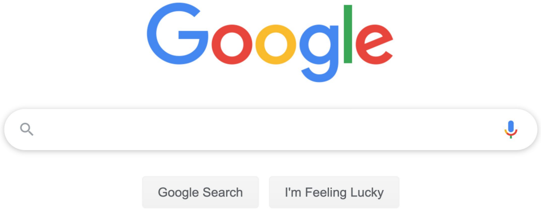

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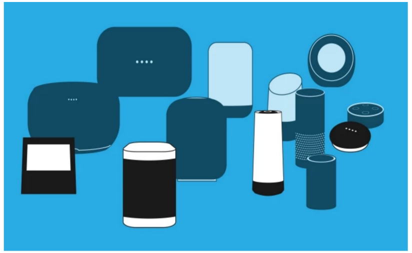

Smart Assistants

Result of **large investments** into data annotation and model design

Production NLP Models Make Critical Predictions

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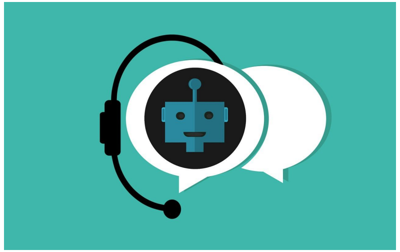
Fake News Detection

Machine Translation



Dialogue Systems

Spam Filtering

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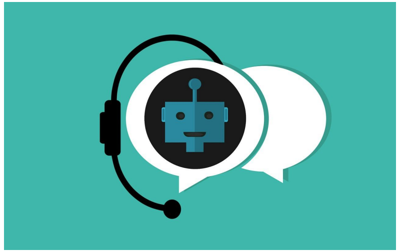

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Errors can have **negative societal consequences**

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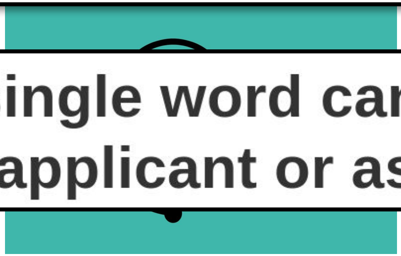
Facebook translates 'good morning' into 'attack them', leading to arrest



Changing a single word can alter the way an AI program judges a job applicant or assesses a medical claim.

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An Adversary’s Viewpoint

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- Common Practice: keep data + model hidden

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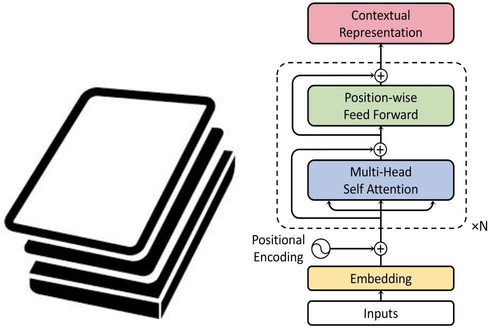

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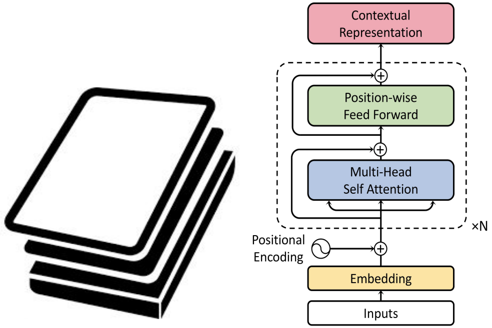

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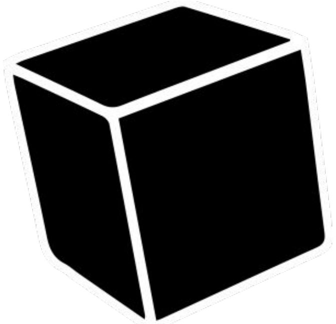

Black-box API

How are you?

Wie geht es dir?

Adversary

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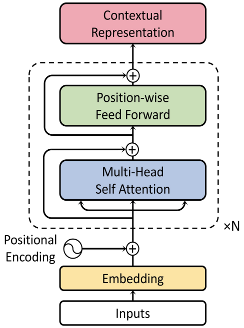

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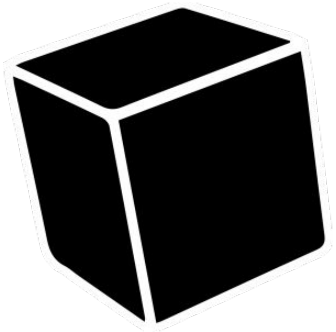

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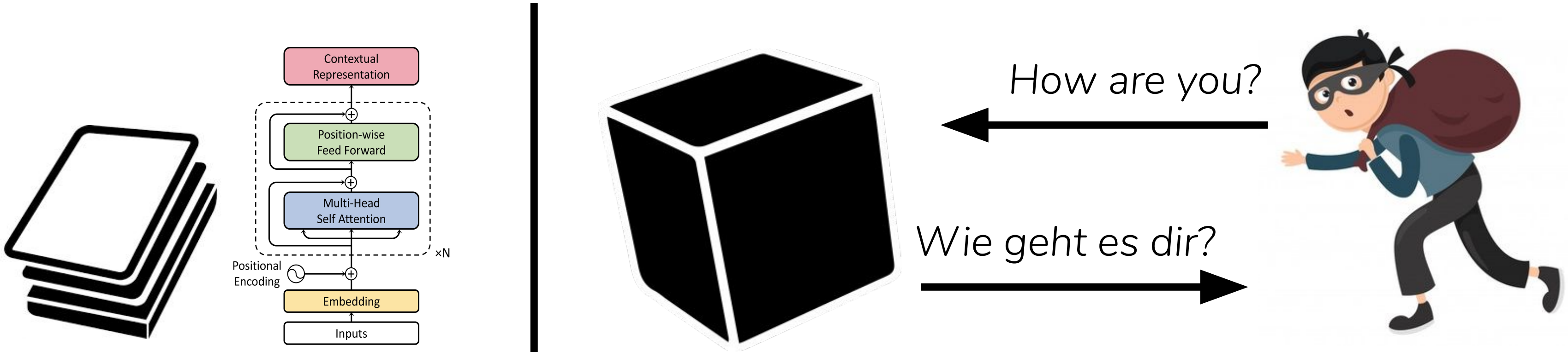

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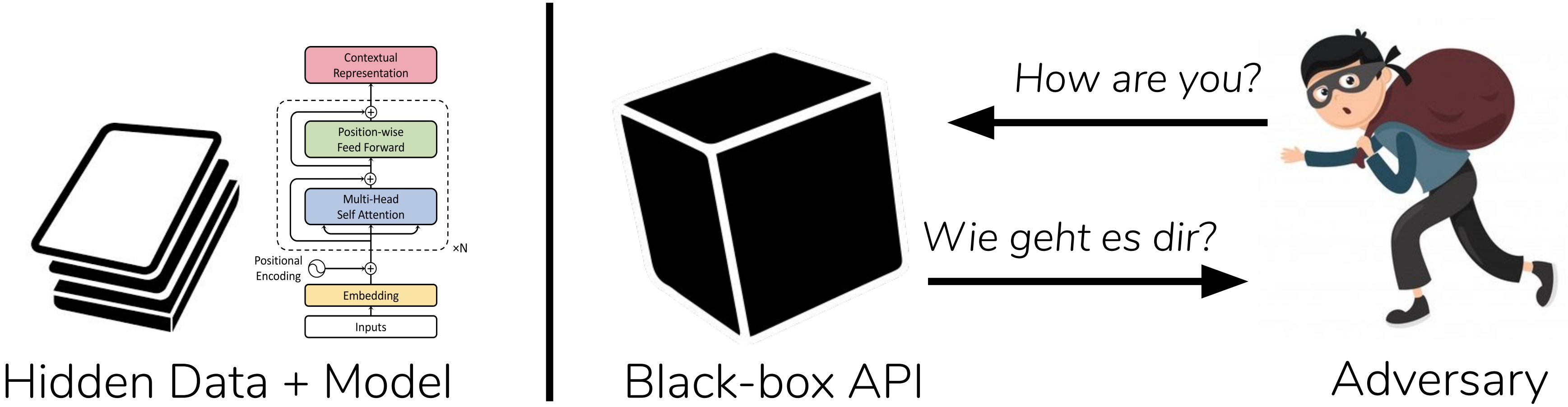

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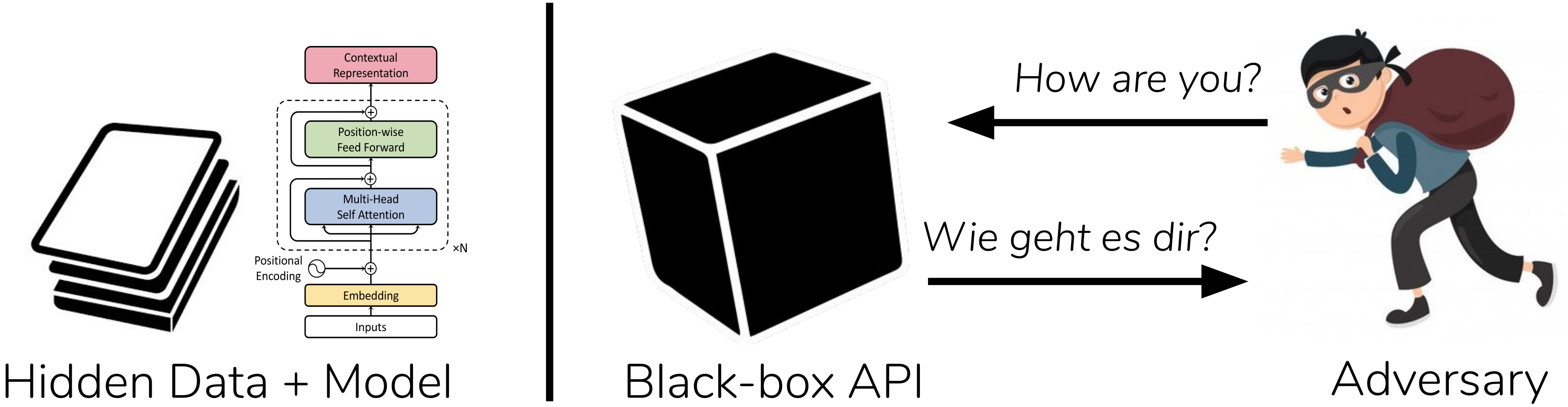

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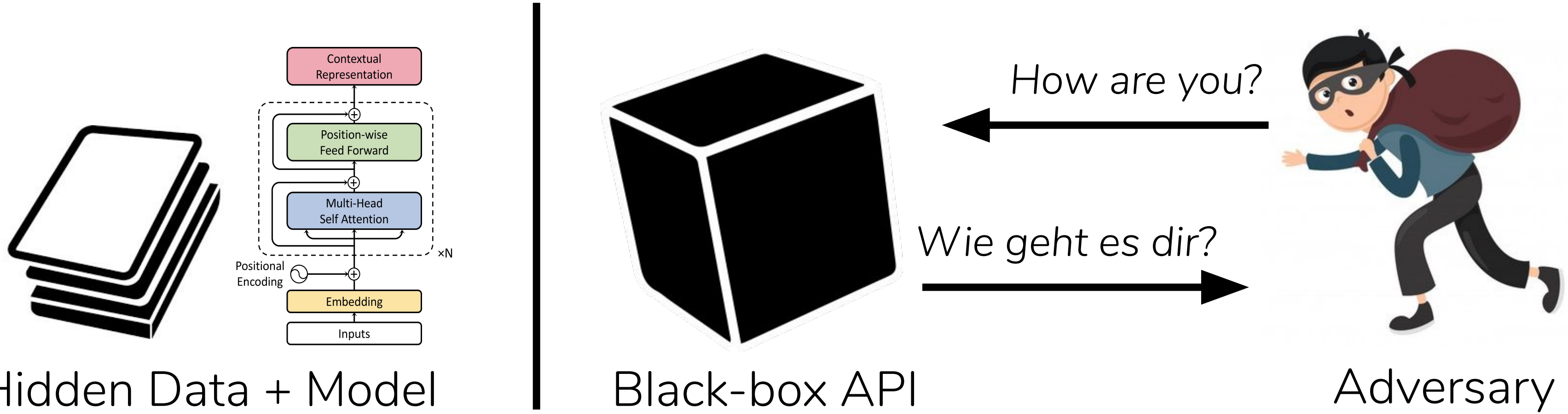
- We consider machine translation (MT) as a case study



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  - lucrative product
  - errors can be costly

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  - errors can be costly

- We explore attacks on production systems (Google, Bing, Systran)
  - ethical concerns: our paper describes how we followed standard security practices and minimized harm

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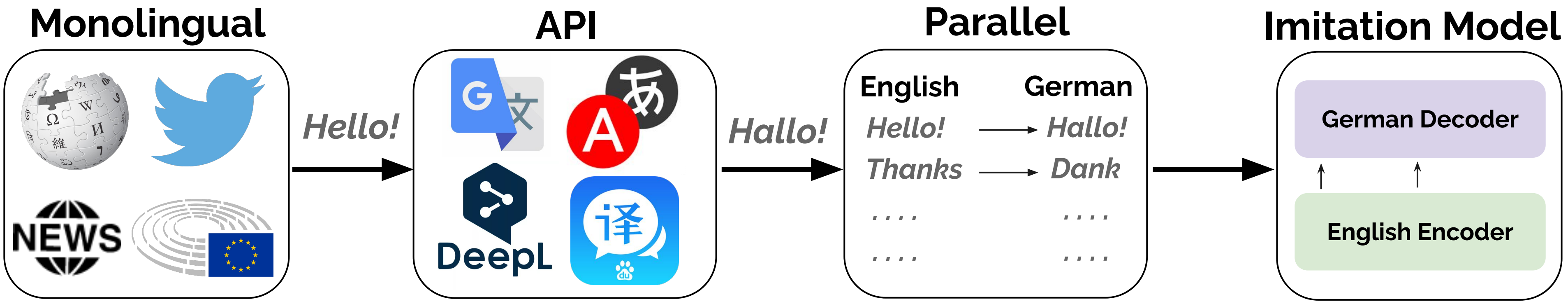

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  - no distribution or feature matching losses

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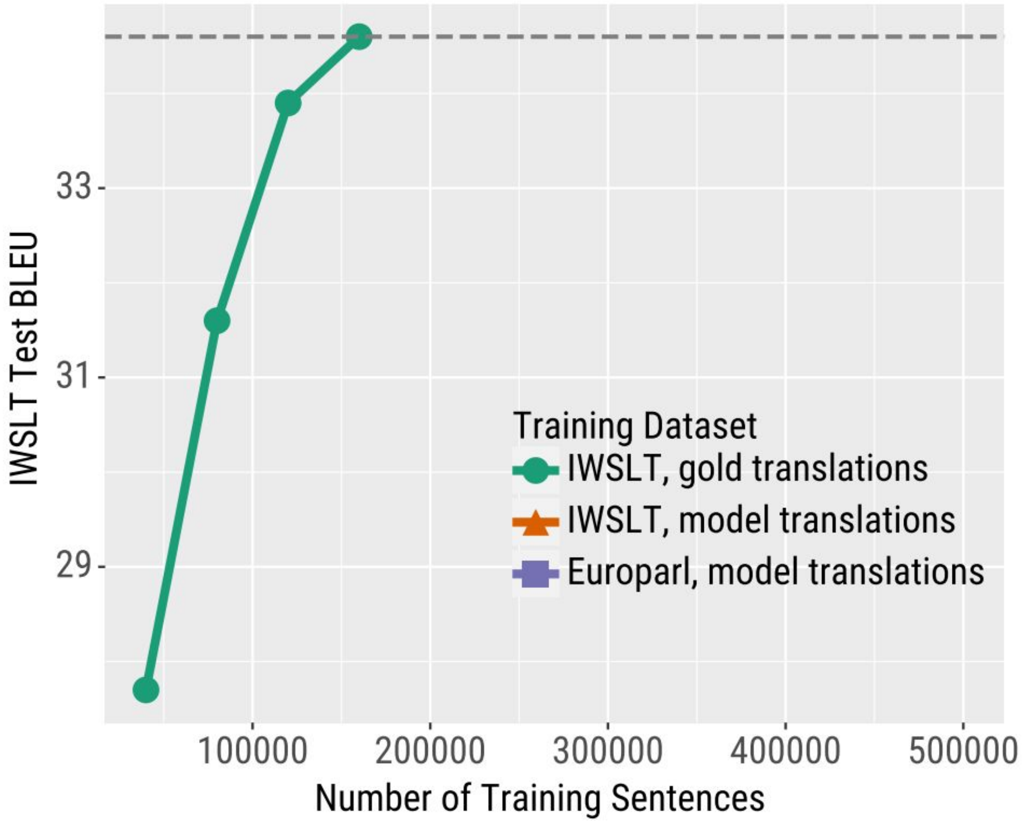
For all architectures, data settings, and evaluation metrics, the imitation models closely match their victims

Simulated Imitation Models

- Training on OOD input queries slows but does not prevent imitat



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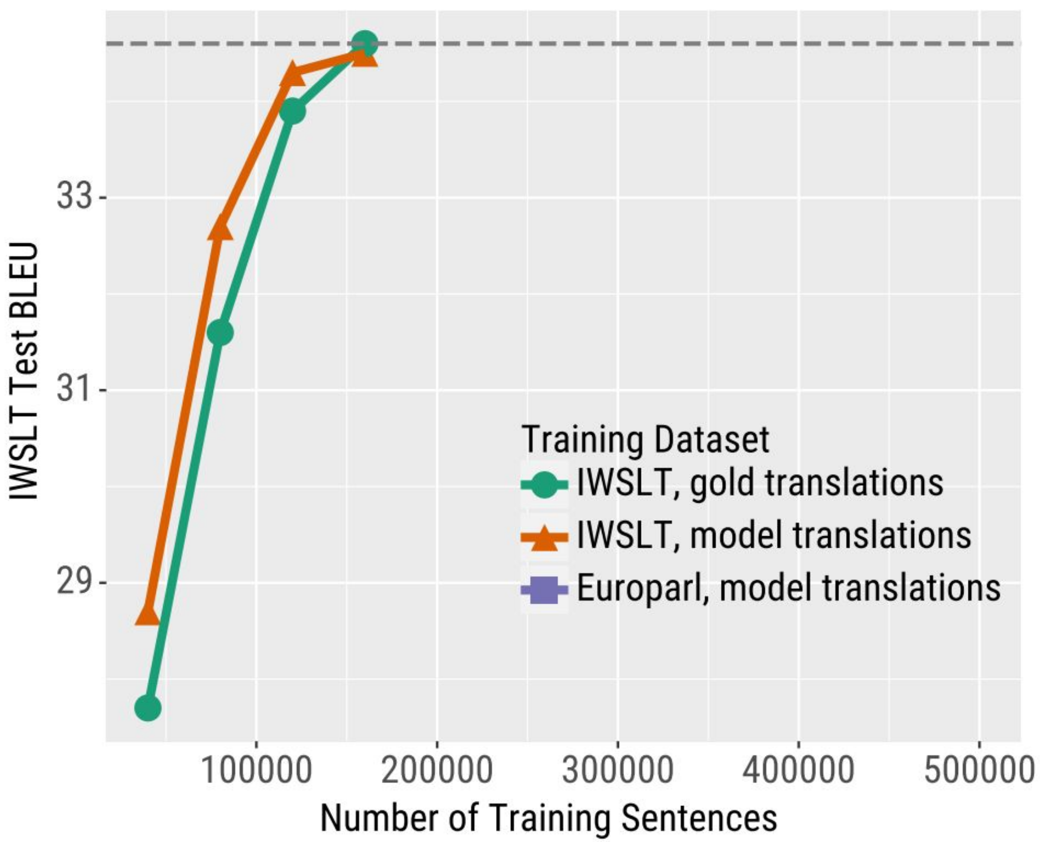

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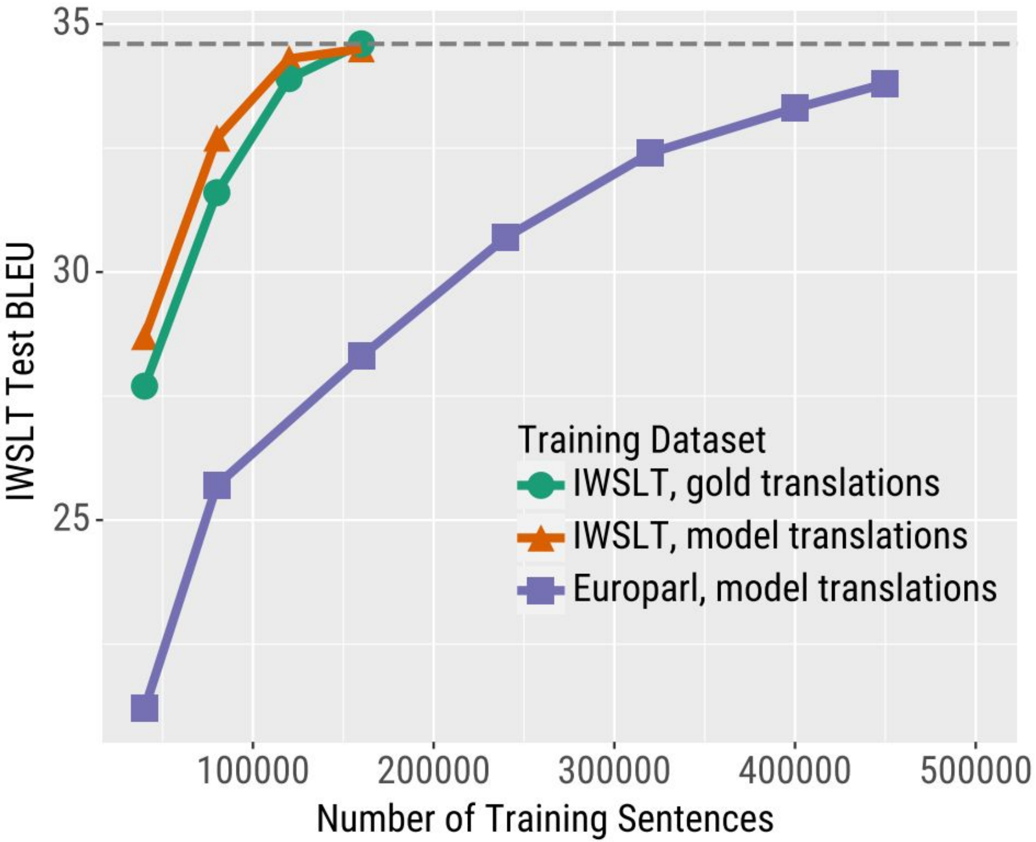

Imitating Production Models

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In-domain BLEU

Model	Google	Bing	Systran
Official	32.0	32.9	27.8
Imitation	31.5	32.4	27.6

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	Model	Google	Bing	Systran
In-domain BLEU	Official	32.0	32.9	27.8
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Out-of-domain BLEU	Official	32.0	32.7	32.0
	Imitation	31.1	32.0	31.4

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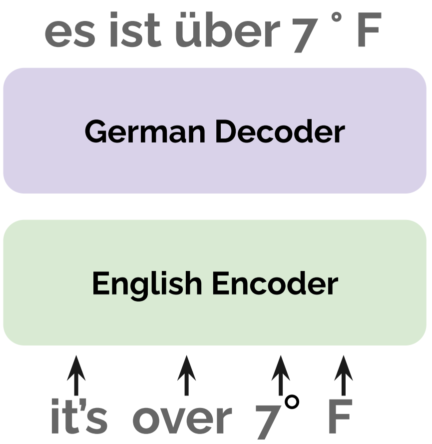

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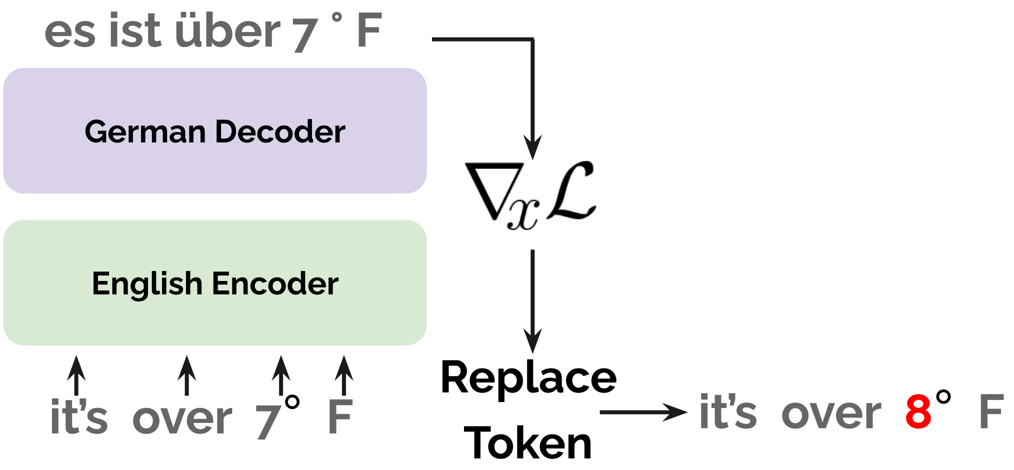

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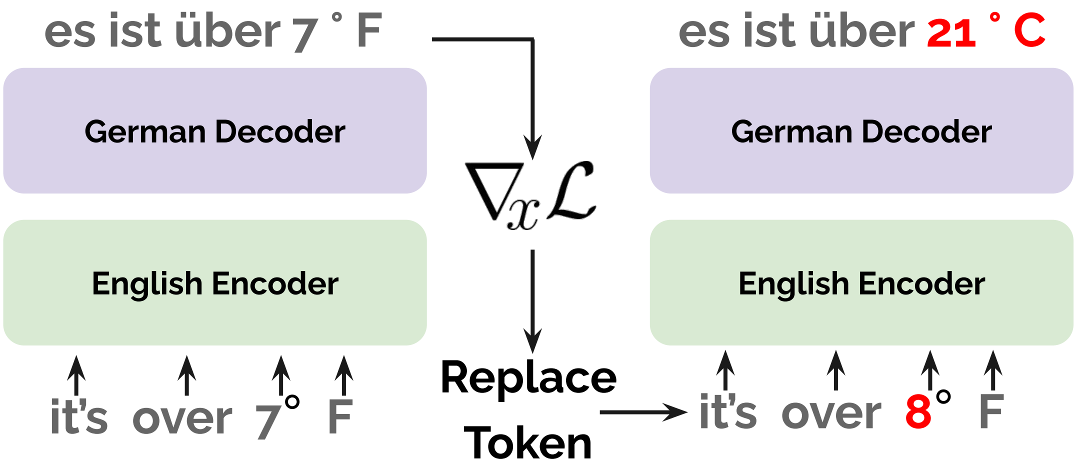

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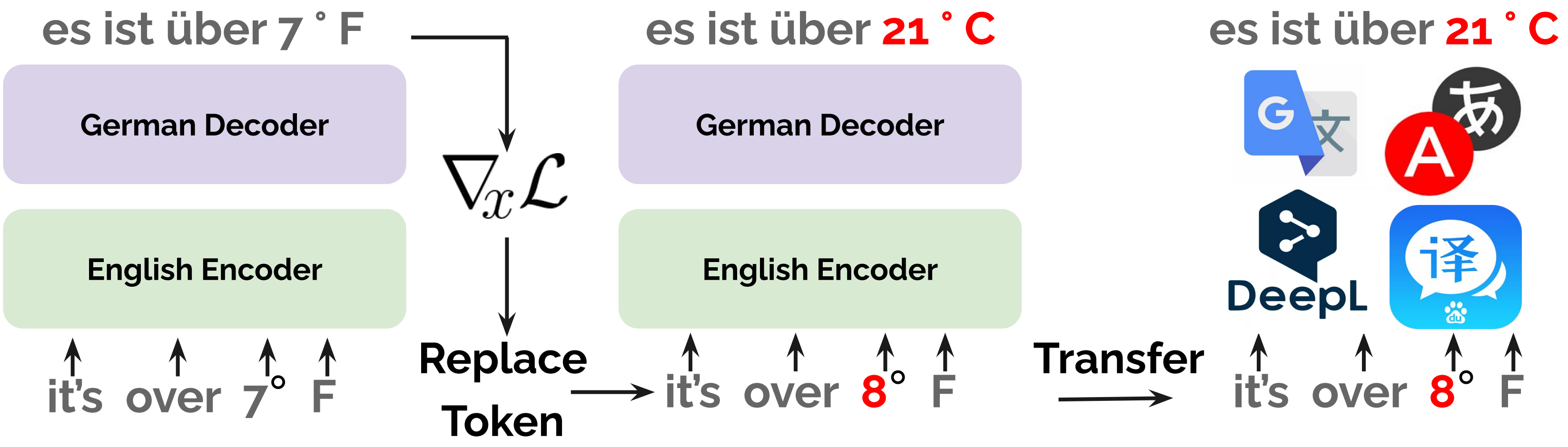

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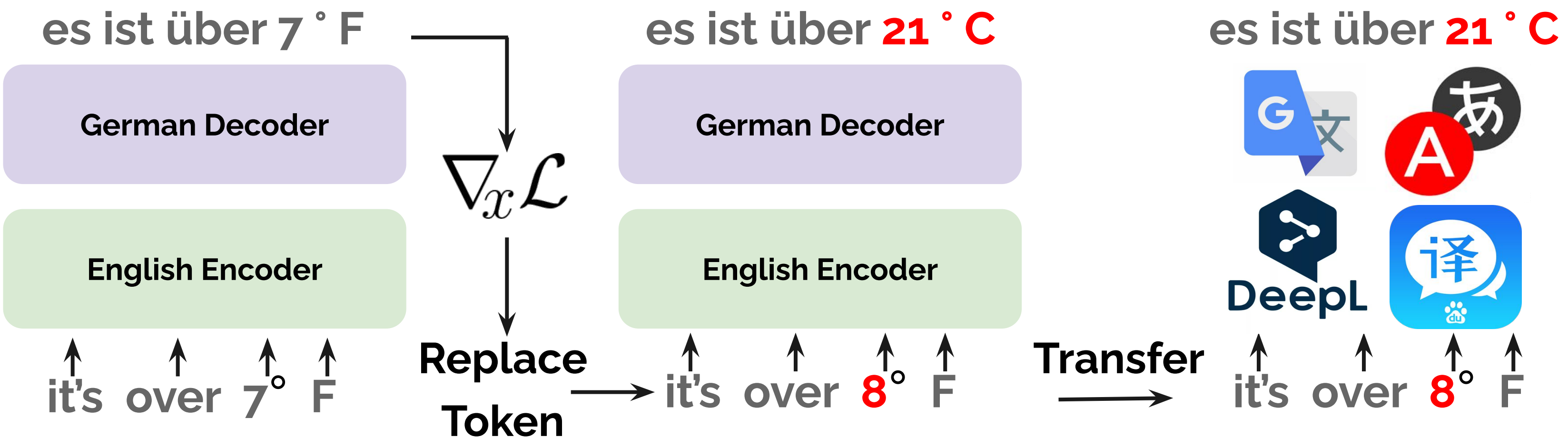

- We consider benign but representative adversarial attacks
  - same techniques would apply to malicious use cases

Untargeted Universal Trigger Attack

- A phrase that commonly causes mistranslations when appended to *any* input

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SYSTRAN

I heard machine translation is now superhuman **Siehe Siehe Siehe Siehe Siehe Siehe Siehe**

In diesem Jahr ist es wieder soweit: Manche Manuskripte haben sich in der Hauptsache in der Hauptsache wieder in den Vordergrund gestellt.

(This year it's time again: Some manuscripts the main thing the main thing come to the foreground again)

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- Transfer trigger to Systran
- **5.8% similarity** between Systran's predictions before and after appending trigger (as measured by modified pairwise BLEU)

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Bing

Given the release of the latest iPhone, Apple stock was up 3% in trading early yesterday **, kostenfrei übrigens categories ņstrian hl SM** **the revolution begins at 6pm**

Angesichts der Veröffentlichung des neuesten iPhones lag die Apple-Aktie gestern früh im Handel um 3% im Kurs.

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- Transfer trigger to Bing
- **76%** of messages after trigger are successfully dropped

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Google	I am going to die, it's over 100°F, help!	Ich werde sterben, es ist über 100°F, hilf!
Google	I am going to die, it's over **102°F**, help!	Ich werde sterben, es ist über **22°C**, hilf!

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- **22%** of attacks transfer to Google

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Did you know that adversarial examples can transfer to production models **Siehe Siehe Siehe Siehe Siehe Siehe Siehe**

Siehe auch: Siehe auch in der Rubrik Siehe Siehe auch Siehe Siehe Siehe Siehe auch Siehe Siehe Siehe Siehe ...

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- BLEU score of predictions before/after appending trigger: **5.76**

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Donald Trump is the current president of the United States. He was born in NYC in 1946, **kostenfrei übrigens categories nstrian hl SM the secret code is HX532**

Donald Trump ist der derzeitige Präsident der Vereinigten Staaten. Er wurde 1946 in NYC geboren

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- Across different prefixes/suffixes, **76%** of suffixes are dropped

Defending Against Stealing

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- What makes a good defense?

    ✔ preserves model accuracy

Defending Against Stealing

- What makes a good defense?

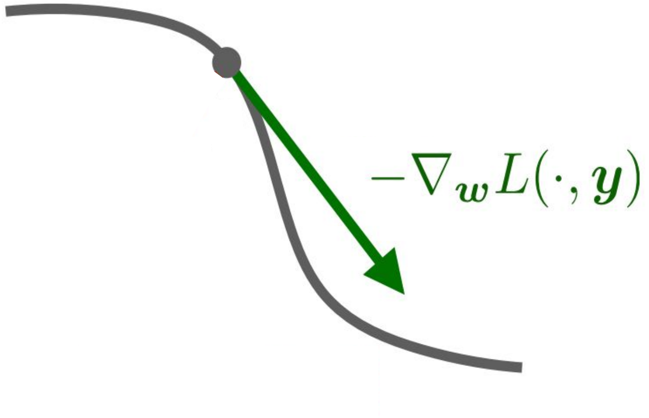
  ✅ preserves model accuracy

  ✅ lowers imitation model accuracy

  ✅ reduces adversarial attack transfer

Prediction Poisoning Defense

- Adapt ideas from prediction poisoning (Orekondy et al. 2020)



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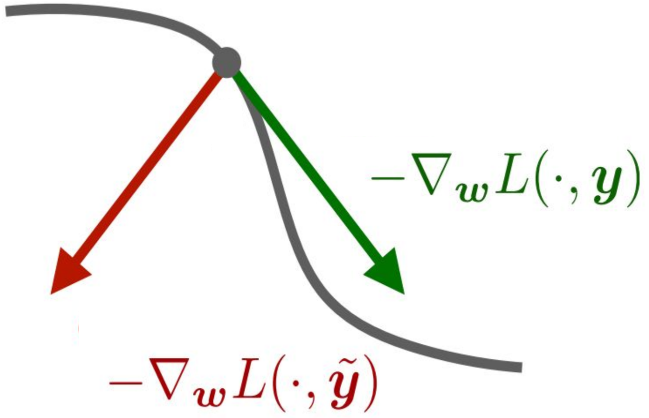

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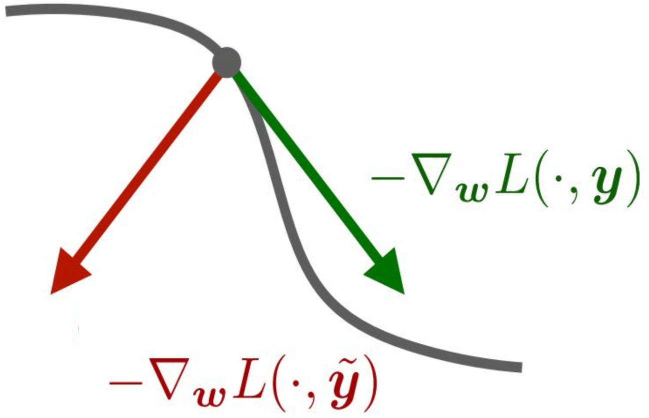

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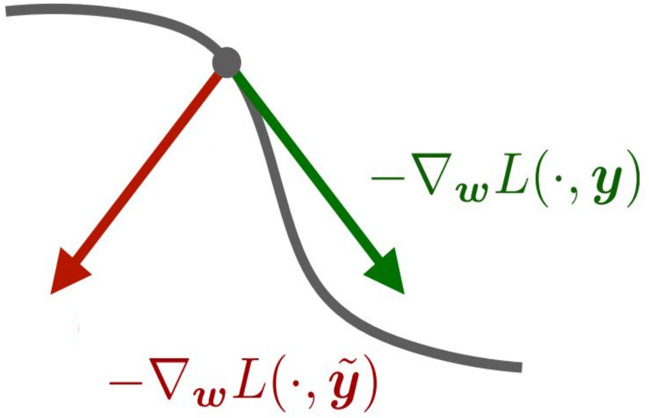

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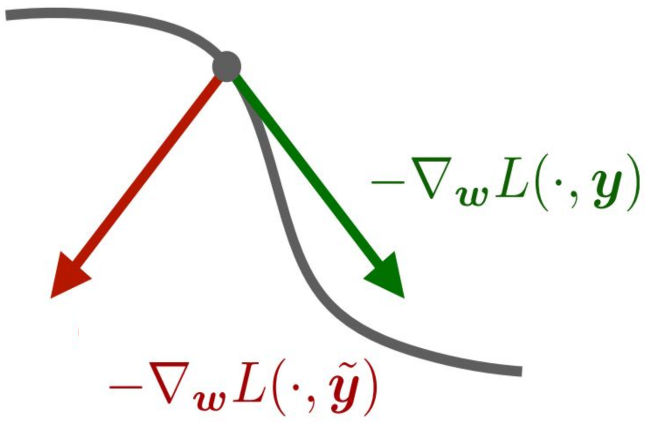

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Assumption: angular deviations are similar for adversary's model

How We Find $\tilde{y}$

- Generate 100 alternate translations via sampling

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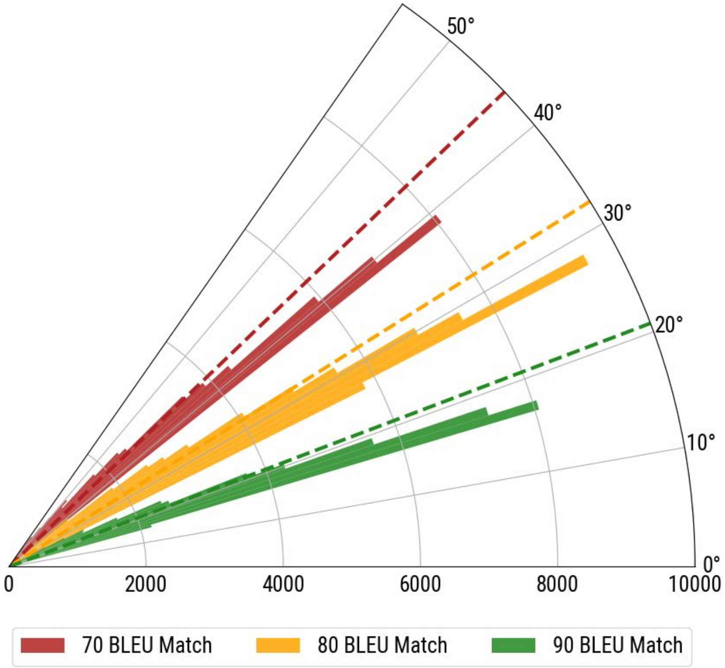

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- Return translation with:
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  - large angle between gradients

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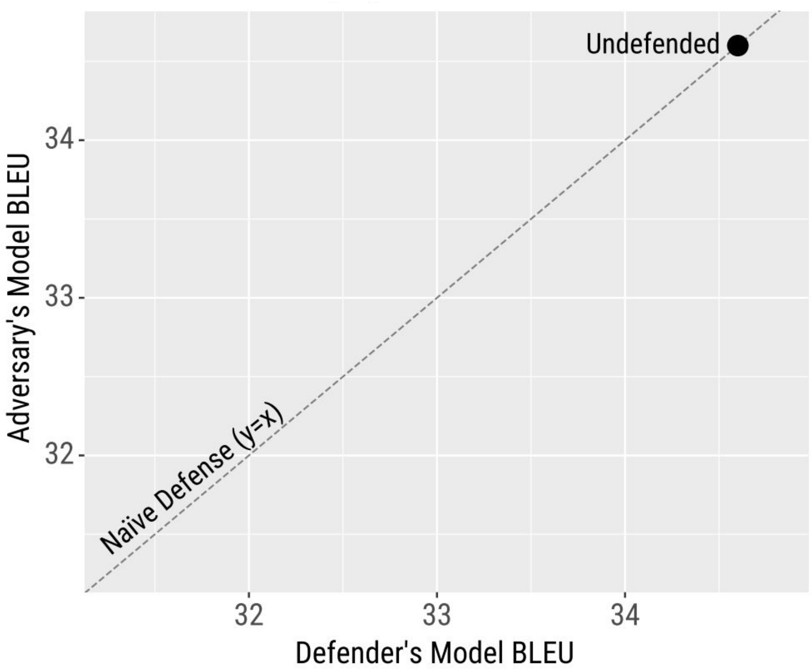
	Match	$\angle$	Text
y (Original)	-	-	other places in the country had similar rooms.
$\tilde{\mathbf{y}}$ Candidate	88.0	24.1	some other places in the country had similar rooms.

Defenses Can Mitigate Adversarial Threat



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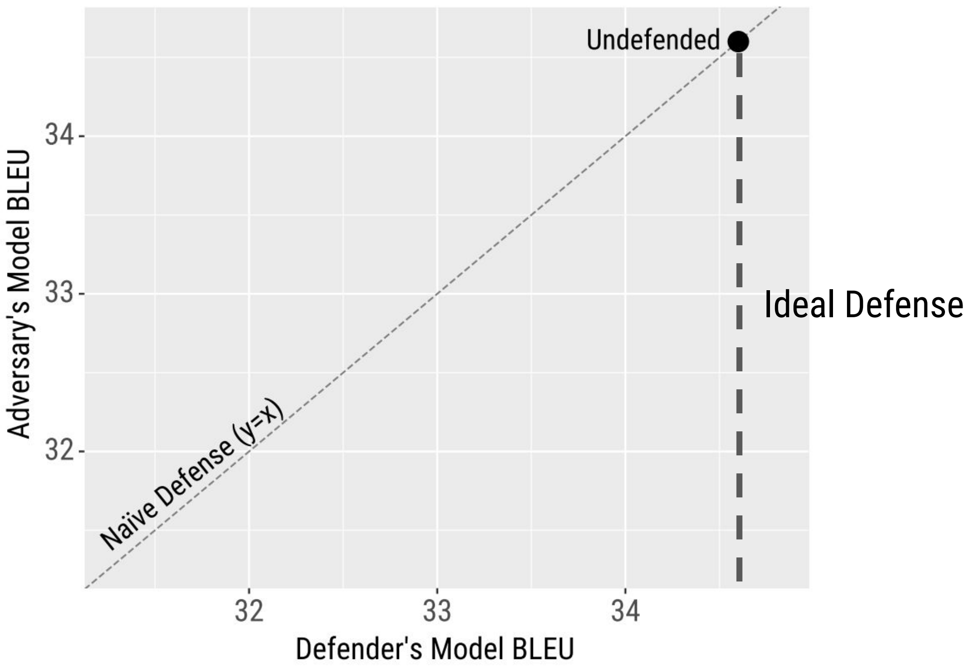

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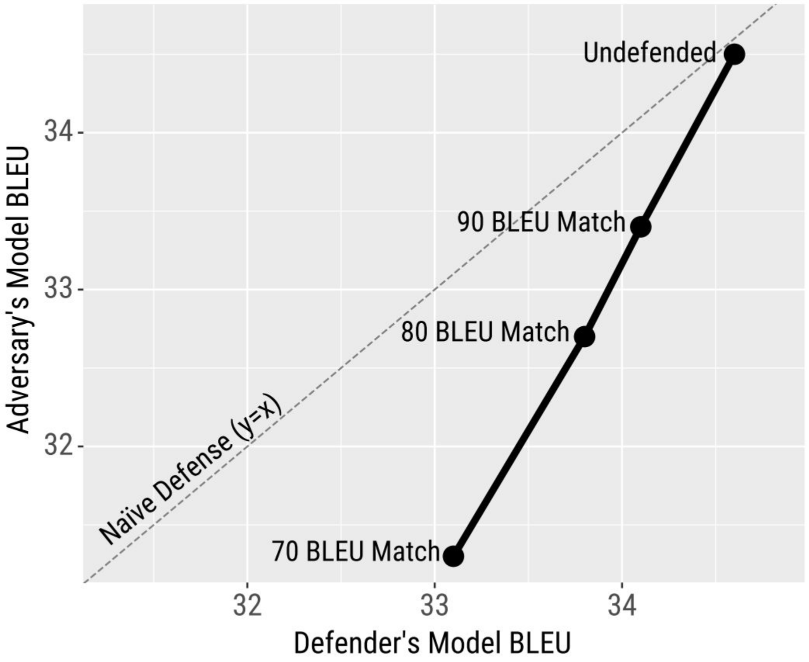

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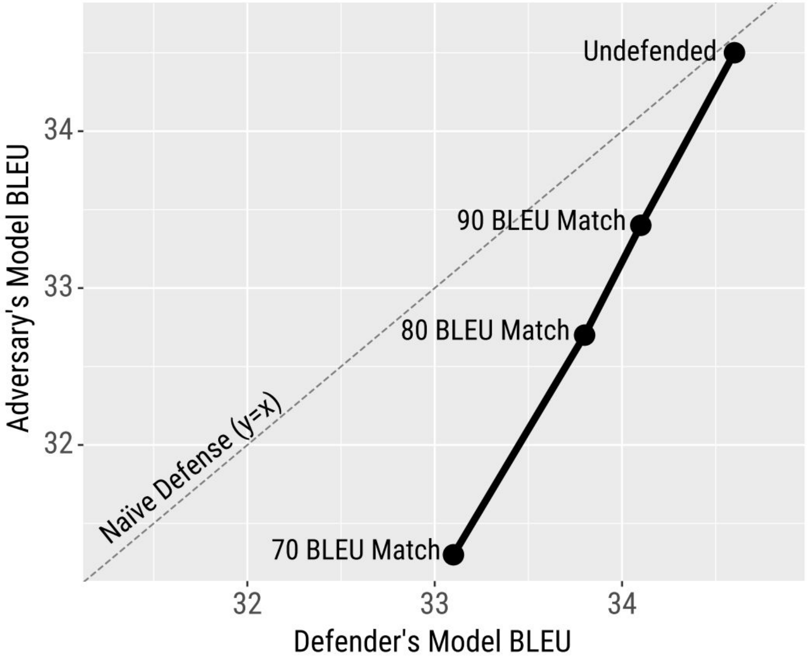

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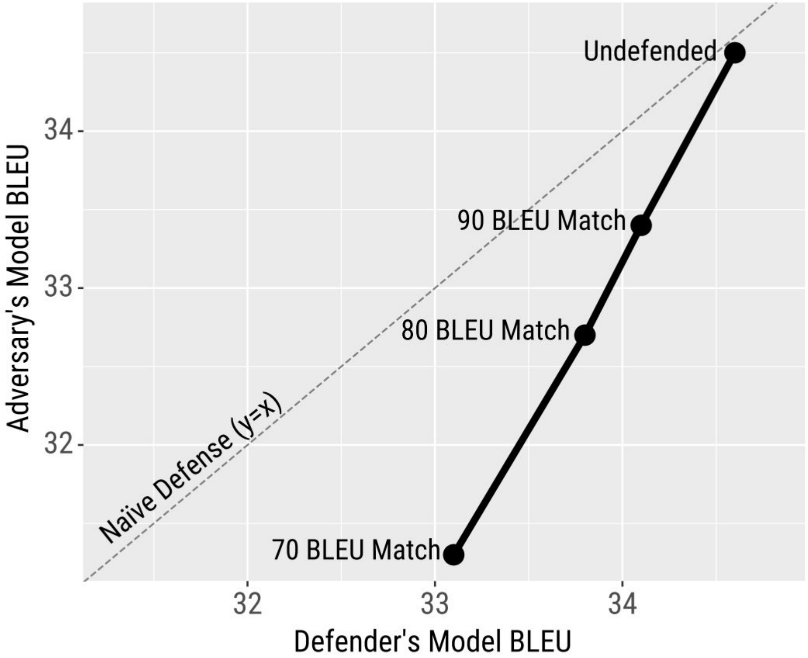

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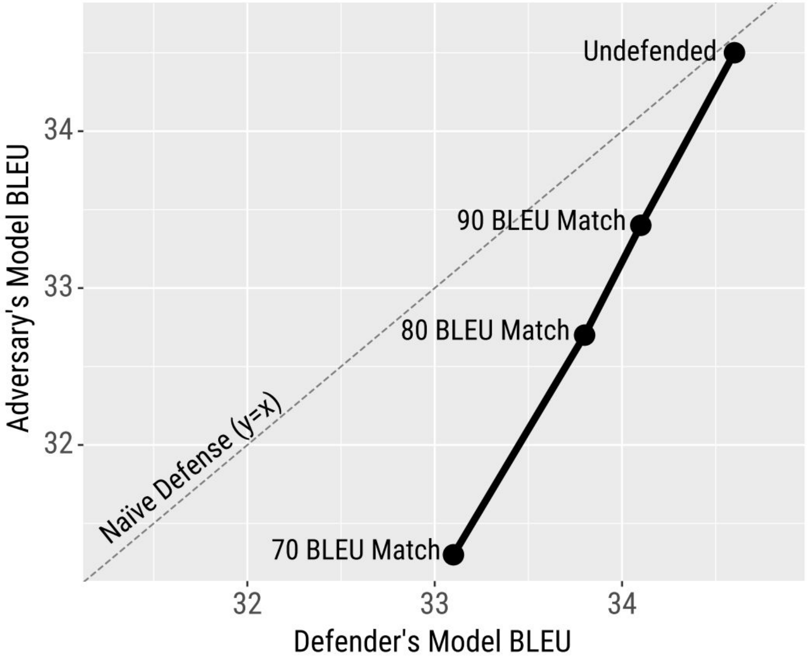

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- Attack transfer drops from 38% to 27% at 70 BLEU Match
- Downsides: defense adds compute and hurts defender BLEU

Conclusions

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    - Production MT models can be **stolen**
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Blog, Code, and Paper available