UNSUPERVISED CIPHER CRACKING USING DISCRETE GANS

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AAU CPH - SW9

Contents

1. Introduction

1. Introduction

Premise of this paper

Can a neural network be trained to deduce withheld ciphers from unaligned text, without the supplementation of preexisting human knowledge?

Historical context

- Decryption was human-guided

Unsupervised learning

- Unpaired bank of ciphertext/plaintext
- No knowledge of vocab frequencies or cipher keys
- Large vocab (200 elements)

2. Key Concepts

2.1 Caesar Shift

PLAIN:	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t	u	v	w	x	y	z
3-SHIFTED:	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t	u	v	w	x	y	z	a	b	c

Example: hello world → khoor zruog

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Example: hello world → khoor zruog

Weakness

- Trivial to solve with frequency analysis

2.2 Vigenère

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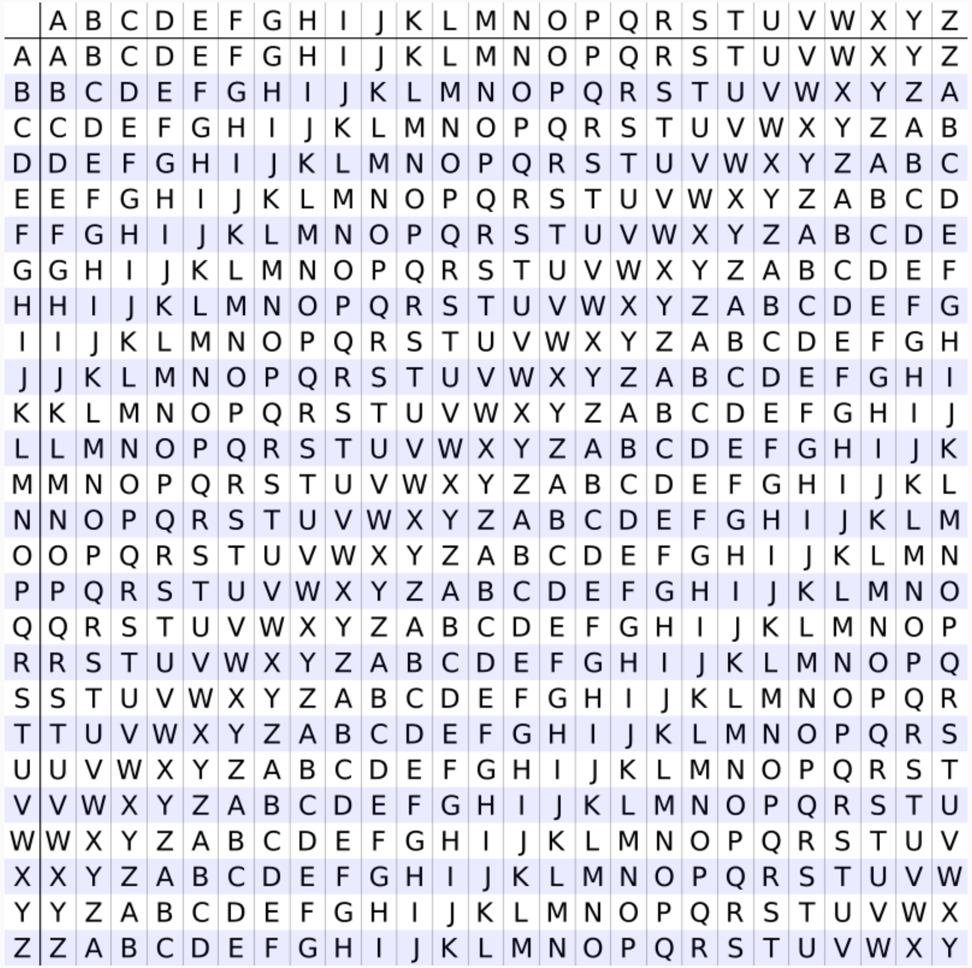
KEY: `soda`

KEYSTREAM: `sodas odaso`

ENCRYPTED: `zsolg krrdr`



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
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B	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	A
C	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	A	B
D	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	A	B	C
E	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	A	B	C	D
F	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	A	B	C	D	E
G	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	A	B	C	D	E	F
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I	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	A	B	C	D	E	F	G	H
J	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	A	B	C	D	E	F	G	H	I
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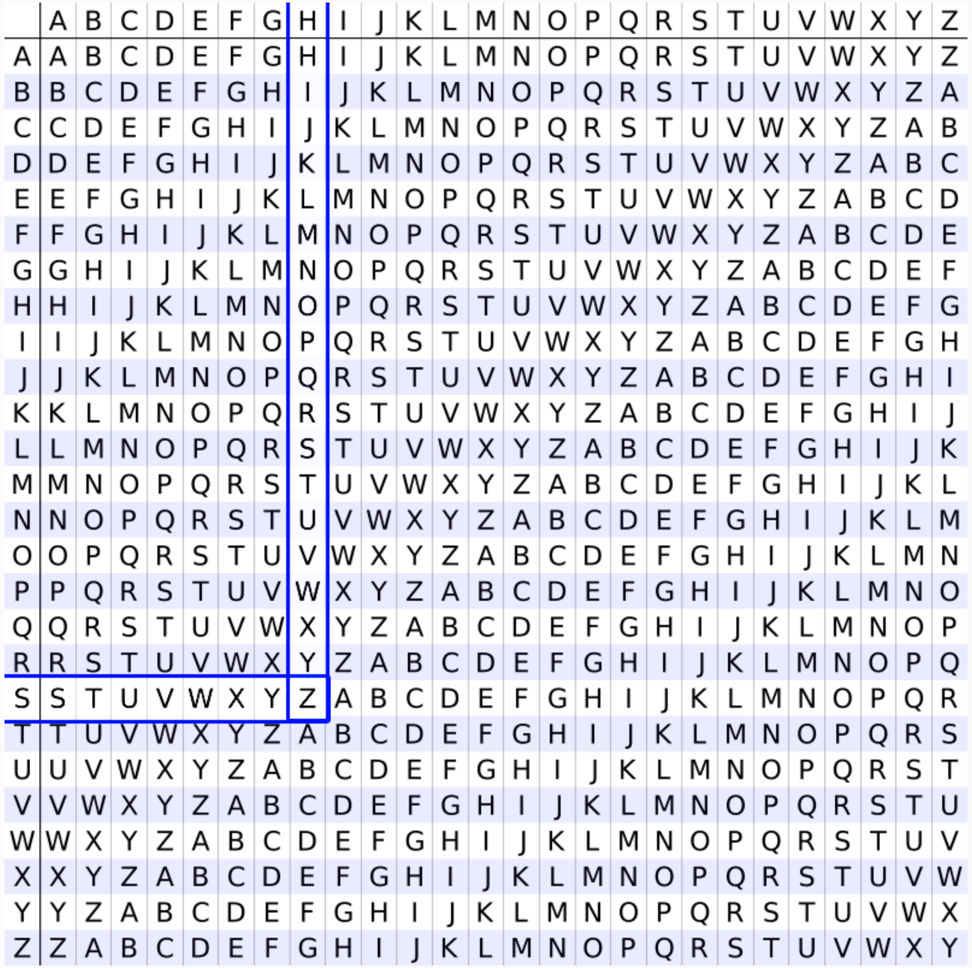

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C	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	A	B
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Y	Y	Z	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X
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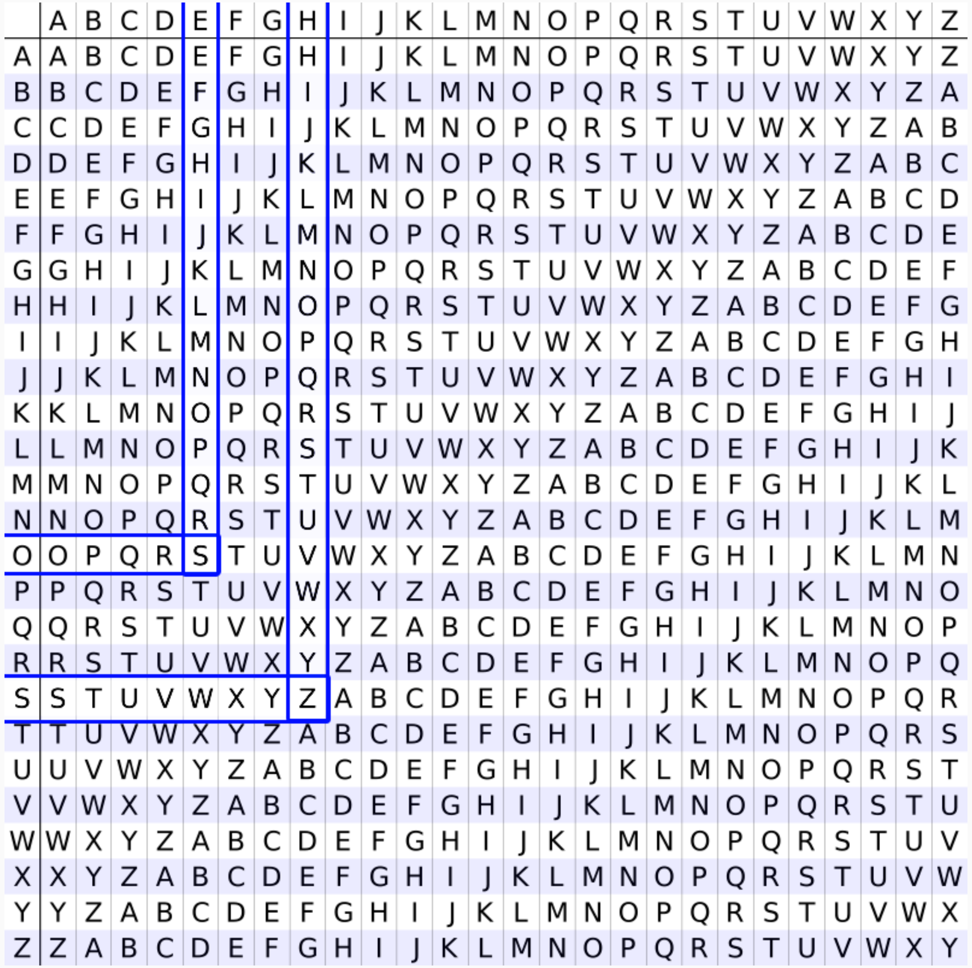

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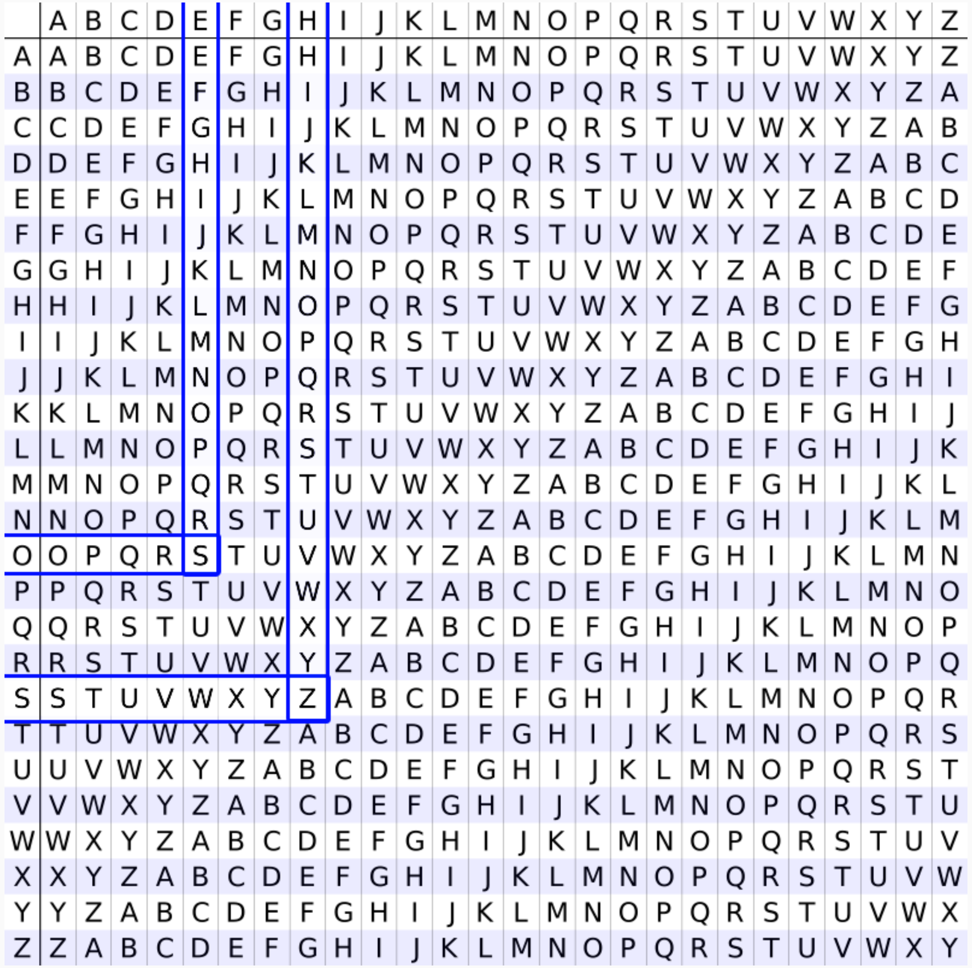
Increased difficulty

- Frequencies are scrambled



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Z	Z	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y

2.3 GAN

Generator

- Attempts to produce convincing samples from data distribution
- Denoted as F

Discriminator

- Tries to distinguish between true and synthetic samples
- Denoted as G

$$D^* = \arg\max_D E_{x\sim\mathcal{X}}[\log D(x)] - E_{z\sim\mathcal{Z}}[\log(1 - D(F(z)))]$$

2.3 GAN

$$D^* = \arg\max_D E_{x\sim\mathcal{X}}[\log D(x)] - E_{z\sim\mathcal{Z}}[\log(1 - D(F(z)))]$$

D^*

- optimal discriminator

$\arg\max_D$

- parameters causing highest possible score

$E_{x\sim\mathcal{X}}$

- Real data

$D(x)$

- Assigned probability
- (e.g. 1 = real, 0 = fake)

$F(z)$

- Generator creating fake text

$1 - D(F(z))$

- Chance of correctly identifying fakes

2.3 GAN

$$D^* = \arg\max_D E_{x\sim\mathcal{X}}[\log D(x)] - E_{z\sim\mathcal{Z}}[\log(1 - D(F(z)))]$$

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$\arg\max_D$

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Vulnerable to mode collapse

- Generator loses diversity - distribution collapses

2.3 GAN

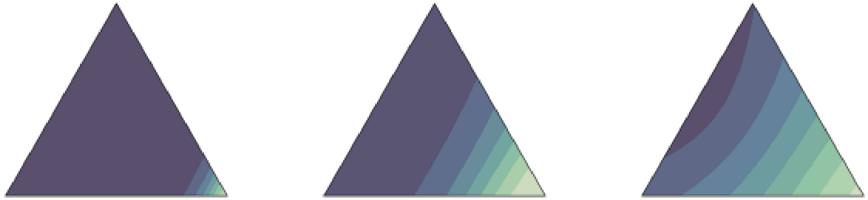


Figure 2: Discriminators trained on the toy example of recognizing the bottom-right corner of a simplex as true data. From left to right the discriminators were regularized using: nothing; WGAN Jacobian norm regularization; and, the relaxed sampling technique.

Original GAN can be too strict

- No helpful feedback

Used by this paper

- Wasserstein Jacobian norm
- Relaxation Sampling

3. Related Work

3.1 CycleGAN

Two distributions

- $\mathcal{X}$ & $\mathcal{Y}$

Two generators

- $F : \mathcal{X} \rightarrow \mathcal{Y}$
- $G : \mathcal{Y} \rightarrow \mathcal{X}$

Two discriminators

- $D_{\mathcal{X}} : \mathcal{X} \rightarrow [0, 1]$
- $D_{\mathcal{Y}} : \mathcal{Y} \rightarrow [0, 1]$

Cycle loss

- L1 Norm - original text vs. round-trip text
- Forces model to be one-to-one

$$\mathcal{L}_{\text{cyc}}(F, G, \mathcal{X}, \mathcal{Y}) =$$

$$E_{x \sim X}[\| G(F(x)) - x \ \|_1] + E_{y \sim Y}[\| F(G(y)) - y \ \|_1]$$

3.1 CycleGAN

Consider the losses together

$$\mathcal{L}(F, G, D_{\mathcal{Y}}, D_{\mathcal{Y}}, \mathcal{X}, \mathcal{Y}) = \underbrace{\mathcal{L}_{\text{GAN}}(F, D_{\mathcal{Y}}, \mathcal{X}, \mathcal{Y})}_{\text{forward pass}} + \underbrace{L_{\text{GAN}}(G, D_{\mathcal{X}}, \mathcal{Y}, \mathcal{X})}_{\text{backward pass}} + \lambda * \mathcal{L}_{\text{cyc}}(F, G, \mathcal{X}, \mathcal{Y})$$

Forward pass

- Generator F: Plaintext to ciphertext for discriminator $D_{\mathcal{Y}}$

Backward pass

- Generator G: Ciphertext to plaintext for discriminator $D_{\mathcal{X}}$

λ

- Hyperparameter - good translator vs good detective

Cycle

- Ensures diversity - avoid mode collapse

4. Ideas & Results

4.1 CipherGAN

Words in embedding space

- Discrete choices do not produce gradients

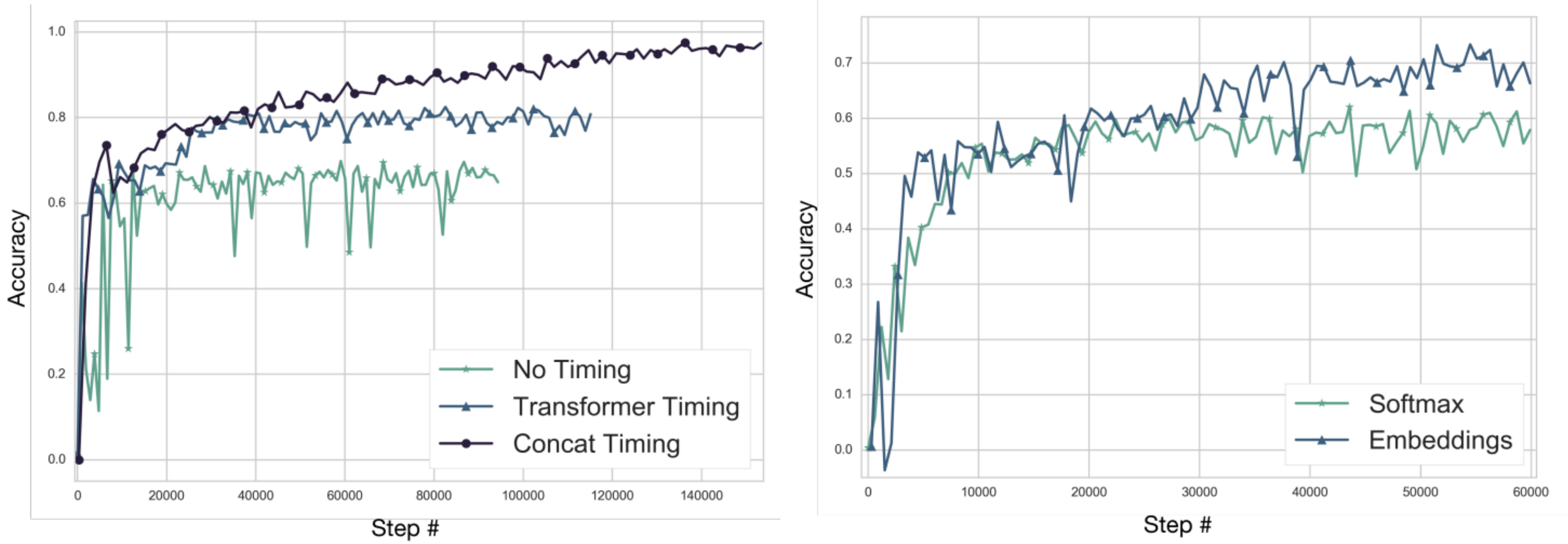


Figure 3: Left: Comparison of different timing techniques for Brown-C Vigenère. Right: Comparison of embedding vs. raw softmax on Brown-W with vocab size of 200.

4.1 CipherGAN

WGAN-GP (Jacobian Norm)

- Limit learning rate of discriminator
- Smooth training signal for generator

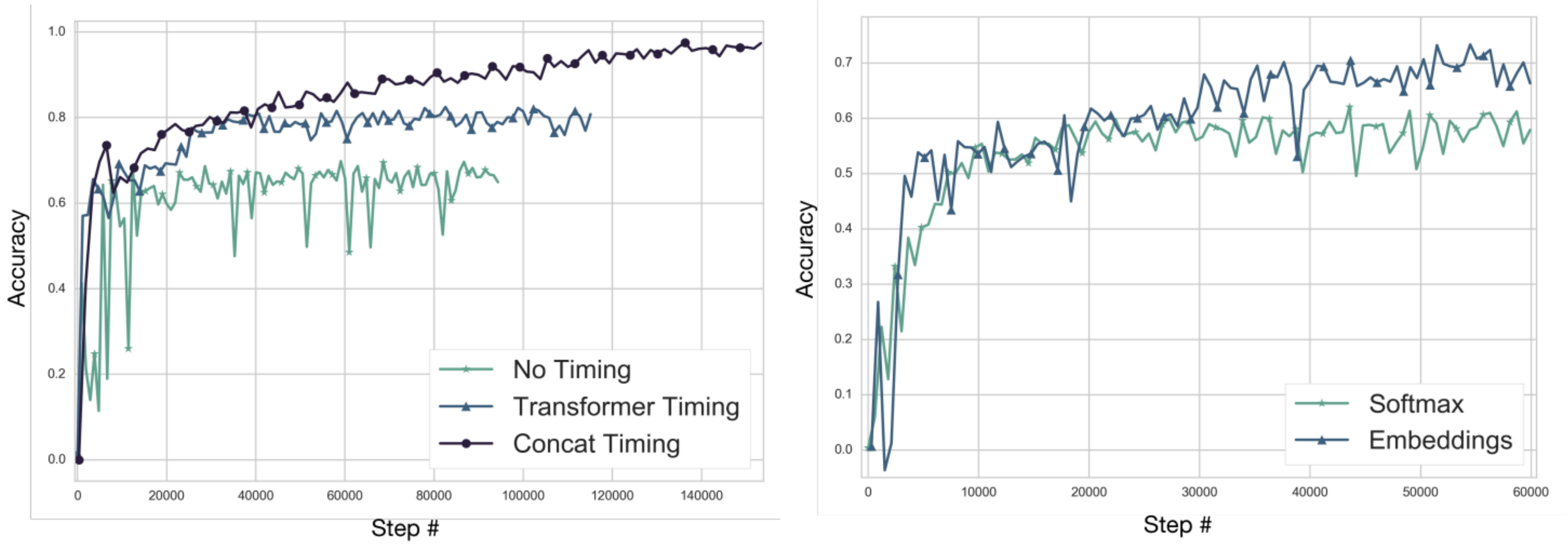


Figure 3: Left: Comparison of different timing techniques for Brown-C Vigenère. Right: Comparison of embedding vs. raw softmax on Brown-W with vocab size of 200.

4.1 CipherGAN

Positional embedding (Timing)

- Vigenère relies on positioning
- Tag each letter with position index

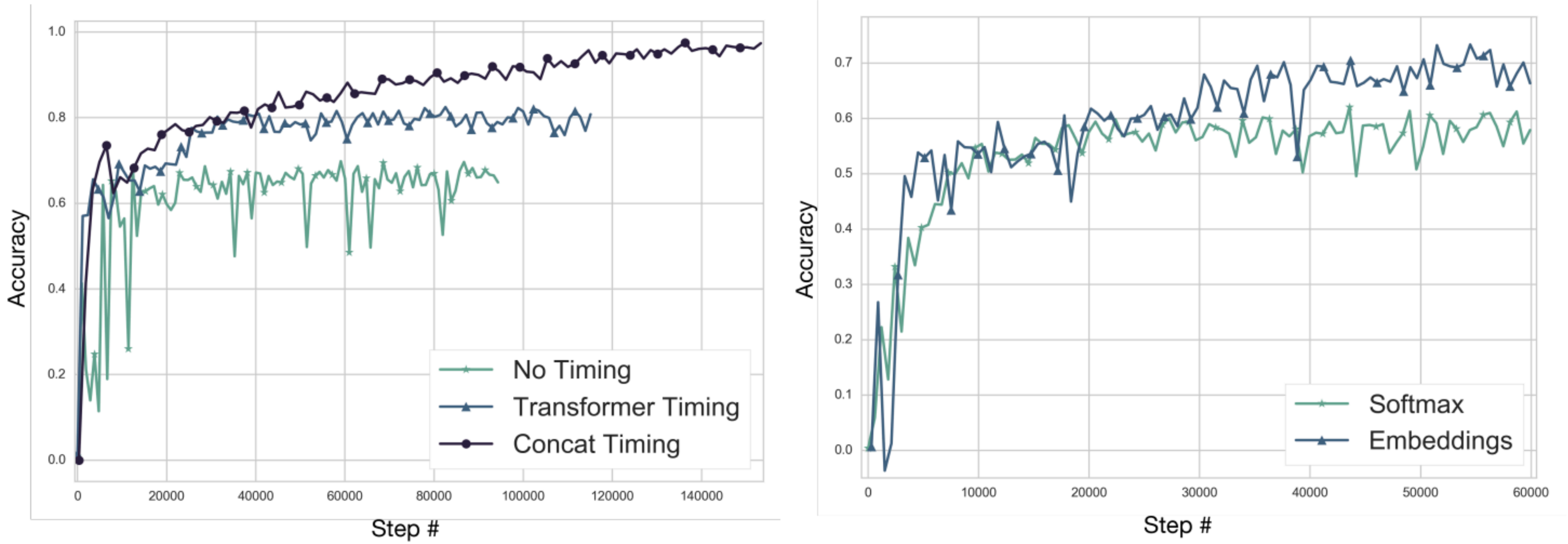


Figure 3: Left: Comparison of different timing techniques for Brown-C Vigenère. Right: Comparison of embedding vs. raw softmax on Brown-W with vocab size of 200.

4.2 Data

Brown English text dataset

- 1st half as CycleGAN $\mathcal{X}$ distribution
- 2nd half as ciphers in $\mathcal{Y}$ distribution

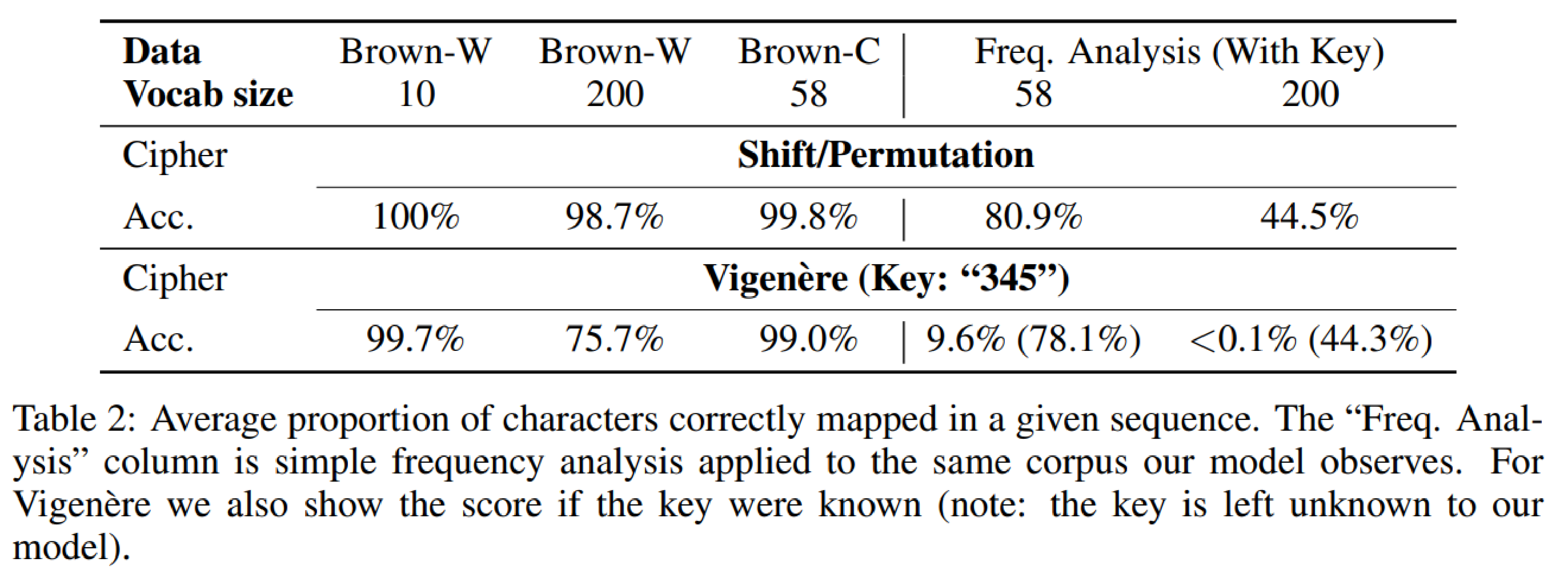
Brown English-Language corpus

- Natural language plaintext
- Over 1 mil. words
- Both word-level and char-level

Brown-W

- Top 200 most frequent words
- Rest is blank

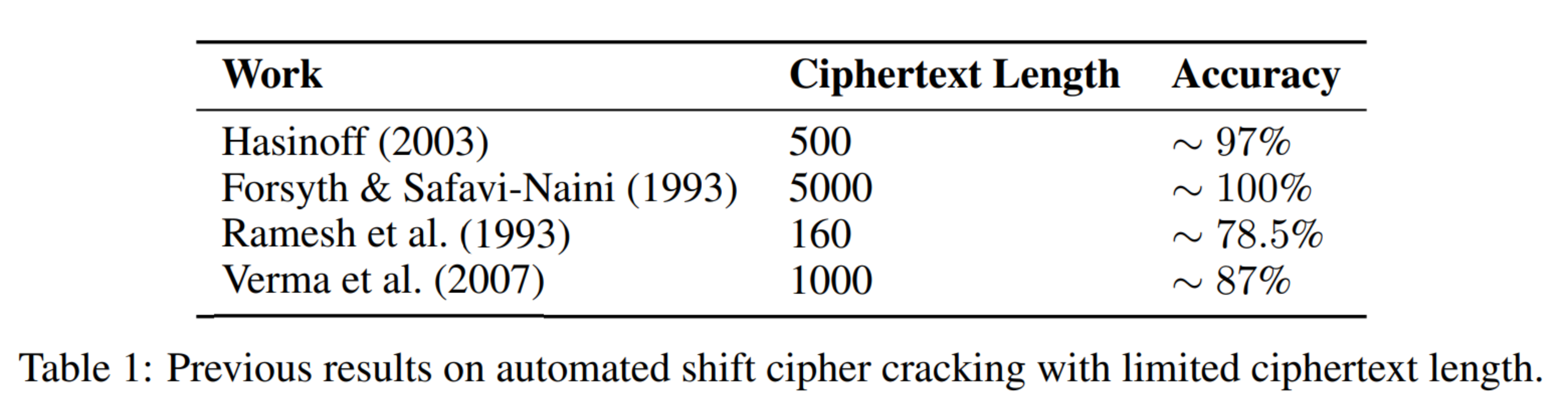
4.3 Results



Data	Brown-W	Brown-W	Brown-C	Freq. Analysis (With Key)	
Vocab size	10	200	58	58	200
Cipher			**Shift/Permutation**		
Acc.	100%	98.7%	99.8%	80.9%	44.5%
Cipher			**Vigenère (Key: "345")**		
Acc.	99.7%	75.7%	99.0%	9.6% (78.1%)	<0.1% (44.3%)

Table 2: Average proportion of characters correctly mapped in a given sequence. The "Freq. Analysis" column is simple frequency analysis applied to the same corpus our model observes. For Vigenère we also show the score if the key were known (note: the key is left unknown to our model).

4.3 Results



Work	Ciphertext Length	Accuracy
Hasinoff (2003)	500	$\sim 97\%$
Forsyth & Safavi-Naini (1993)	5000	$\sim 100\%$
Ramesh et al. (1993)	160	$\sim 78.5\%$
Verma et al. (2007)	1000	$\sim 87\%$

Table 1: Previous results on automated shift cipher cracking with limited ciphertext length.

5. Criticism

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Why not test on a real cipher?

- E.g. Civil War Vigenere cipher
- Real ciphers has typos, etc.

Sequence length bottleneck

- 200 chars is short!
- GANs are likely to become unstable

Missing other neural baselines

Missing related work section

5. Criticism

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Missing other neural baselines

Missing related work section

Current better models - (like CausalLM)

- We know this because we are from the future 😄

6. Relevance to my project

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Homophonic Substitution Ciphers

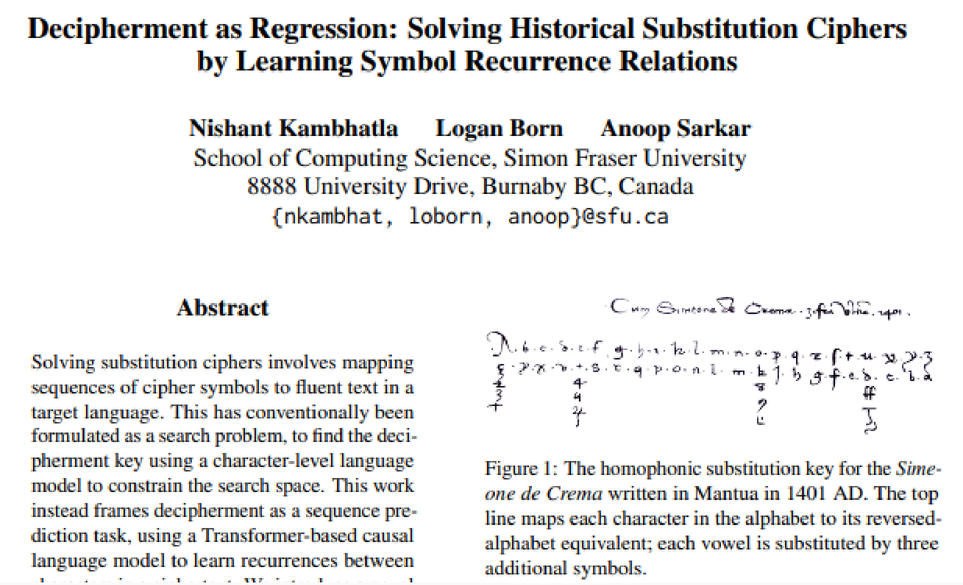
- 1-to-many mappings
- English
- Only lowercase letters
- No spaces

Comparative Study

- Embeddings
- Heuristics
- Seq-2-Seq

Increase sequence length with CausalLM

- Linear attention?
- Flash attention?



Decipherment as Regression: Solving Historical Substitution Ciphers by Learning Symbol Recurrence Relations

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Abstract

Solving substitution ciphers involves mapping sequences of cipher symbols to fluent text in a target language. This has conventionally been formulated as a search problem, to find the decipherment key using a character-level language model to constrain the search space. This work instead frames decipherment as a sequence prediction task, using a Transformer-based causal language model to learn recurrences between

Figure 1: The homophonic substitution key for the *Simeone de Crema* written in Mantua in 1401 AD. The top line maps each character in the alphabet to its reversed-alphabet equivalent; each vowel is substituted by three additional symbols.