REPORT

Minor Project

Securing Data Communication with Adversarial Neural Cryptography

Minor Group 4
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Project Guide
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Certificate

This is to certify that this report entitled **"Securing Data Communication with Adversarial Neural Cryptography"** submitted towards partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in Electrical Engineering by

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is a bonafide record of the group's own work carried out during the **Minor Project** under my supervision and guidance. The candidates have fulfilled all the prescribed requirements.

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Preface

The field of Machine Learning research is one of the fastest changing and most lucrative fields of research today. With modern techniques boasting levels of efficacy never seen before, it is evidently one of the highest sought-after fields. We started to venture into this field of technology with our academic career and have been interested in using these techniques in applications currently unheard of. With that said, our interests also veer towards web technologies and the world of communication. It is with that goal that we set about melding the two fields of cybersecurity and machine learning in new ways.

This work was produced as an academic report for the B.Tech Final Year Minor Project and is a summary of the background, work done and results obtained from experiments performed over the course of a semester. Parts of this work are citations and quotes from other academic articles and may bear resemblance in the wording. We do not claim the work presented in these papers as our own and have no intent to plagiarise. This work may not be used as an academic reference due to the lack of a peer review before publication of this report. There may be errors, miscalculations or otherwise inadvertent mistakes which may be misleading or harmful.

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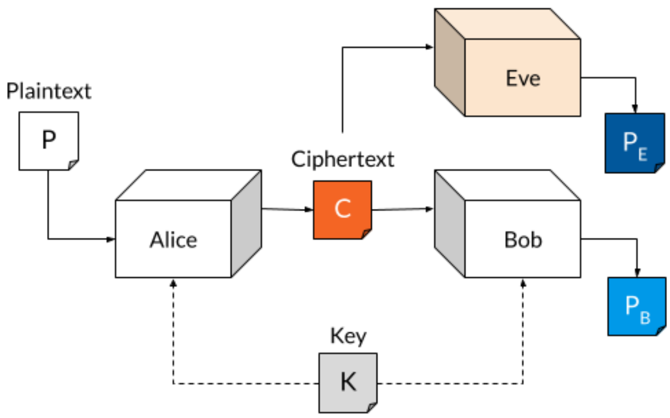

Abstract

In this project, we demonstrate that neural networks can learn to protect communications, and build a network which can encrypt and decrypt bit-strings. The learning does not require prescribing a particular set of cryptographic algorithms, nor indicating ways of applying these algorithms. We do not prescribe specific cryptographic algorithms to these neural networks; instead, we train end-to-end, adversarially. We demonstrate that the neural networks can learn how to perform forms of encryption and decryption, and also how to apply these operations selectively in order to meet confidentiality goals.

1 Introduction

As neural networks are applied to increasingly complex tasks, they are often trained to meet end-to-end objectives that go beyond simple functional specifications. These objectives include, for example, generating realistic images [1] and solving multiagent problems.

Cryptography is broadly concerned with algorithms and protocols that ensure the secrecy and integrity of information. Cryptographic mechanisms are typically described as programs or Turing machines. Attackers are also described in those terms, with bounds on their complexity and on their chances of success. A mechanism is deemed secure if it achieves its goal against all attackers. For instance, an encryption algorithm is said to be secure if no attacker can extract information about plaintexts from ciphertexts. Modern cryptography provides rigorous versions of such definitions.

Neural networks are generally not meant to be great at cryptography. Famously, the simplest neural networks cannot even compute XOR, which is basic to many cryptographic algorithms. Nevertheless, as was demonstrated in the seminal paper on this subject [2] by Abadi et. al in 2016, neural networks can learn to protect the confidentiality of their data from other neural networks: they discover forms of encryption and decryption, without being taught specific algorithms for these purposes.

Knowing how to encrypt is seldom enough for security and privacy. Interestingly, neural networks can also learn what to encrypt in order to achieve a desired secrecy property while maximizing utility. Thus, when we wish to prevent an adversary from seeing a fragment of a plaintext, or from estimating a function of the plaintext, encryption can be selective, hiding the plaintext only partly.

1.1 Objective

The goal of this **Minor Project** is to examine concept of Adversarial Neural Cryptography and implement the algorithms and models described in the relevant literature. Advancing these lines of work, we show that neural networks can learn to protect their communications in order to satisfy a policy specified in terms of an adversary. The resulting cryptosystems are generated automatically by learning to prevent an adversary from learning information about the transmission.

From the perspective of cryptography, it relates to big themes such as privacy and discrimination. While we embrace a playful, exploratory approach, we do so with the hope that it will provide insights useful for further work on these topics.

1.2 Literature Review

Classical cryptography may be able to support some applications along these lines. In particular, homomorphic encryption enables inference on encrypted data (Xie et al, 2014; Gilad-Bachrach et al, 2016).

Prior work at the intersection of machine learning and cryptography has focused on the generation and establishment of cryptographic keys [3], and on corresponding attacks (Klimov et al, 2002). In contrast, our work takes these keys for granted, and focuses on their use; a crucial, new element in our work is the reliance on adversarial goals and training.

More broadly, from the perspective of machine learning, our work relates to the application of neural networks to multiagent tasks, mentioned above, and to the vibrant research on generative models and on adversarial training (Denton et al, 2015; Salimans et al, 2016; Nowozin et al, 2016; Chen et al, 2016; Ganin et al, 2015).

1.2.1 Inferences from Review

- It is possible to synchronize two networks while being loosely connected.
- It is possible to use GANs such that they are able to encrypt text.
- An agent will only be as strong as the environment it's put in.
- Although a NN might not be able to decipher an encrypted message, it might be trivial for a human.

2 Adversarial Neural Networks

The concept of **adversarial learning** comes from the field of **Game Theory,** the branch of mathematics concerned with the analysis of strategies for dealing with competitive situations where the outcome of a participant's choice of action depends critically on the actions of other participants. Game theory has been applied to contexts in war, business, and biology.

2.1 The Nash equilibrium

Consider a game between two adversaries. In this simple game, both players can choose strategy A, to receive a fixed reward, or strategy B, to receive a fixed penalty. Logically, both players choose strategy A and receive a reward. If you revealed one's strategy to the other and vice versa, you see that no player deviates from the original choice. Knowing the other player's move means little and doesn't change either player's behaviour. This outcome represents a **Nash equilibrium.**

Nash equilibrium is named after its inventor, John Nash, an American mathematician. It is considered one of the most important concepts of game theory, which attempts to determine mathematically and logically the actions that participants of a game should take to secure the best outcomes for themselves.

2.2 Generative Adversarial Networks

Generative Adversarial Networks, or GANs for short, are an approach to generative modelling using deep learning methods, such as convolutional neural networks.

GANs are based on the concept of Nash Equilibrium in that the method of training a network isnt derived from labelled data, but from a process of trying to win against another neural network. The system consists of a **Generator** and a **Discriminator** which are two neural networks.

The Generator G produces a fake sample $G(z)$ from a noise sample z. The Discriminator D is given the fake and real samples $G(z)$ and x randomly and has to output a probability which says how likely is it that the current example is fake.

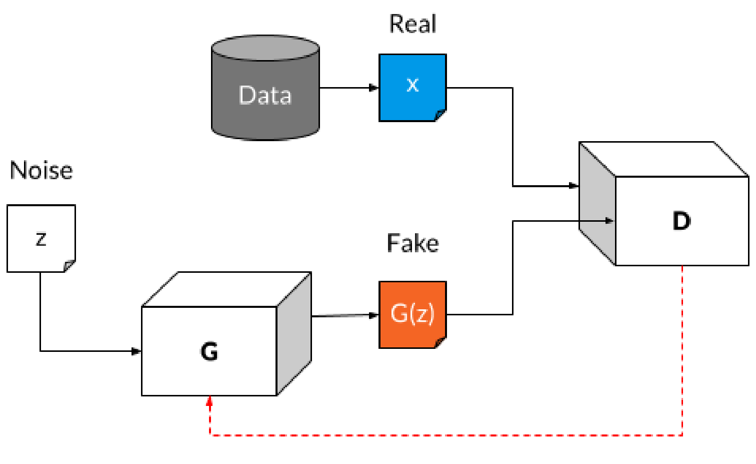

Figure 1: Basic GAN

The loss of the discriminator (i.e. how wrong D is at finding a fake) is what drives the learning of the generator. If the discriminator is very good at finding a fake, the generator has to work harder and harder to produce a better fake that can fool the discriminator. This makes the generator very good at producing fakes. After the training, the discriminator is usually discarded and the generator is used by itself.

The adversarial modelling framework is most straightforward to apply when the models are both multilayer perceptrons. To learn the generators distribution p_g over data x, we define a prior on input noise variables $p_z(z)$, then represent a mapping to data space as $G(z;\theta_g)$, where G is a differentiable function represented by a multilayer perceptron with parameters θ_g. We also define a second multilayer perceptron $D(x;\theta_d)$ that outputs a single scalar. $D(x)$ represents the probability that x came from the data rather than p_g.

We train D to maximize the probability of assigning the correct label to both training examples and samples from G. We simultaneously train G to minimize $log(1 - D(G(z)))$. In other words, D and G play the following two-player **minimax game** with value function

$$V(G, D)_{minGmaxD} = \mathbb{E}_{x\sim p(x)} \log D(x) + \mathbb{E}_{z\sim Q(z)} \log[1 - D(G(z))]$$

GANs are a clever way of training a generative model by framing the problem as a supervised learning problem with two sub-models: the generator model that we train to generate new examples, and the discriminator model that tries to classify examples as either real (from the domain) or fake (generated). The two models are trained together in a zero-sum game, adversarial, until the discriminator model is fooled about half the time, meaning the generator model is generating plausible examples.

GANs are an exciting and rapidly changing field, delivering on the promise of generative models in their ability to generate realistic examples across a range of problem domains, most notably in image-to-image translation tasks such as translating photos of summer to winter or day to night, and in generating photorealistic photos of objects, scenes, and people that even humans cannot tell are fake.

3 Basics of Cryptography

Modern cryptography is heavily based on mathematical theory and computer science practice; cryptographic algorithms are designed around computational hardness assumptions, making such algorithms hard to break in practice by any adversary. It is theoretically possible to break such a system, but it is infeasible to do so by any known practical means. These schemes are therefore termed computationally secure; theoretical advances, e.g., improvements in integer factorization algorithms, and faster computing technology require these solutions to be continually adapted. There exist information-theoretically secure schemes that provably cannot be broken even with unlimited computing poweran example is the one-time padbut these schemes are more difficult to use in practice than the best theoretically breakable but computationally secure mechanisms.

Until modern times, cryptography referred almost exclusively to **encryption**, which is the process of converting ordinary information (called plaintext) into unintelligible form (called ciphertext). **Decryption** is the reverse, in other words, moving from the unintelligible ciphertext back to plaintext.

A cipher is a pair of algorithms that create the encryption and the reversing decryption. The detailed operation of a cipher is controlled both by the algorithm and in each instance by a "key". The key is a secret (ideally known only to the communicants), usually a short string of characters, which is needed to decrypt the ciphertext.

Formally, a "cryptosystem" is the ordered list of elements of finite possible plaintexts, finite possible cyphertexts, finite possible keys, and the encryption and decryption algorithms which correspond to each key. Keys are important both formally and in actual practice, as ciphers without variable keys can be trivially broken with only the knowledge of the cipher used and are therefore useless (or even counter-productive) for most purposes.

3.1 Public Key Encryption

Public-key cryptography, or asymmetric cryptography, is a cryptographic system that uses pairs of keys: public keys, which may be disseminated widely, and private keys, which are known only to the owner. The generation of such keys depends on cryptographic algorithms based on mathematical problems to produce one-way functions. Effective security only requires keeping the private key private; the public key can be openly distributed without compromising security.

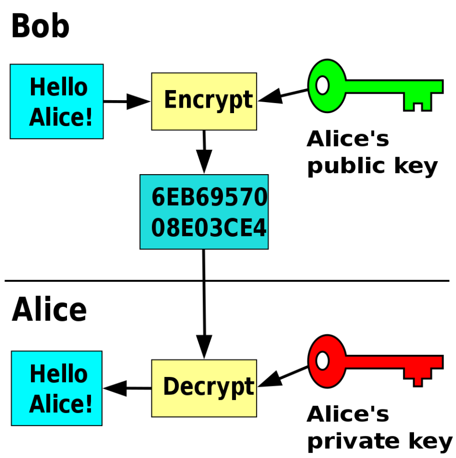

Figure 2: Public Key Encryption mechanism

In such a system, any person can encrypt a message using the receiver's public key, but that encrypted message can only be decrypted with the receiver's private key. This allows, for instance, a server to generate a cryptographic key intended for symmetric-key cryptography, then use a client's openly-shared public key to encrypt that newly-generated symmetric key.

Now, the server can send this encrypted symmetric key on insecure channels to the client, and only the client can decrypt it using the client's private key pair to the public key used by the server to encrypt this message. With the client and server both having the same symmetric key now, they can safely transition to symmetric key encryption to securely communicate back and forth on otherwise-insecure channels. This has the advantage of not having to manually pre-share symmetric keys, while also gaining the higher data throughput advantage of symmetric-key cryptography over asymmetric key cryptography.

With public-key cryptography, robust authentication is also possible. A sender can combine a message with a private key to create a short digital signature on the message. Anyone with the sender's corresponding public key can combine the same message and the supposed digital signature associated with it to verify whether the signature was valid, i.e. made by the owner of the corresponding private key.

3.2 Symmetric Key Encryption

Symmetric-key cryptography refers to encryption methods in which both the sender and receiver share the same key (or, less commonly, in which their keys are different, but related in an easily computable way).

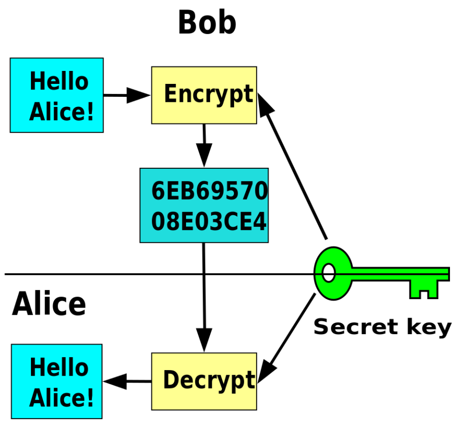

Figure 3: Symmetric Key Encryption mechanism

Symmetric key ciphers are implemented as either block ciphers or stream ciphers. A block cipher enciphers input in blocks of plaintext as opposed to individual characters, the input form used by a stream cipher.

Cryptographic hash functions are a third type of cryptographic algorithm. They take a message of any length as input, and output a short, fixed length hash, which can be used in (for example) a digital signature. For good hash functions, an attacker cannot find two messages that produce the same hash. MD4 is a long-used hash function that is now broken; MD5, a strengthened variant of MD4, is also widely used but broken in practice. Cryptographic hash functions are used to verify the authenticity of data retrieved from an untrusted source or to add a layer of security.

The US National Security Agency developed the Secure Hash Algorithm series of MD5-like hash functions: SHA-0 was a flawed algorithm that the agency withdrew; SHA-1 is widely deployed and more secure than MD5, but cryptanalysts have identified attacks against it; the SHA-2 family improves on SHA-1, but is vulnerable to clashes as of 2011; and the US standards authority thought it "prudent" from a security perspective to develop a new standard to "significantly improve the robustness of NIST's overall hash algorithm toolkit." [4] Thus, a hash function design competition was meant to select a new U.S. national standard, to be called SHA-3, by 2012.

The competition ended on October 2, 2012 when the NIST announced that Keccak would be the new SHA-3 hash algorithm. Unlike block and stream ciphers that are invertible, cryptographic hash functions produce a hashed output that cannot be used to retrieve the original input data.

3.3 One Time Pad Algorithm

In cryptography, the one-time pad (OTP) is an encryption technique that cannot be cracked, but requires the use of a one-time pre-shared key the same size as, or longer than, the message being sent. In this technique, a plaintext is paired with a random secret key (also referred to as a one-time pad). Then, each bit or character of the plaintext is encrypted by combining it with the corresponding bit or character from the pad using modular addition.

The resulting ciphertext will be impossible to decrypt [5] or break if the following four conditions are met:

- The key must be truly random.
- The key must be at least as long as the plaintext.
- The key must never be reused in whole or in part.
- The key must be kept completely secret.

It has also been proven that any cipher with the property of perfect secrecy must use keys with effectively the same requirements as OTP keys. Digital versions of one-time pad ciphers have been used by nations for critical diplomatic and military communication, but the problems of secure key distribution have made them impractical for most applications.

3.4 Neural Cryptography

Neural cryptography is a branch of cryptography dedicated to analyzing the application of stochastic algorithms, especially artificial neural network algorithms, for use in encryption and cryptanalysis.

Artificial neural networks are well known for their ability to selectively explore the solution space of a given problem. This feature finds a natural niche of application in the field of cryptanalysis. At the same time, neural networks offer a new approach to attack ciphering algorithms based on the principle that any function could be reproduced by a neural network, which is a powerful proven computational tool that can be used to find the inverse-function of any cryptographic algorithm.

The ideas of mutual learning, self learning, and stochastic behavior of neural networks and similar algorithms can be used for different aspects of cryptography, like public-key cryptography, solving the key distribution problem using neural network mutual synchronization, hashing or generation of pseudo-random numbers.

Another idea is the ability of a neural network to separate space in non-linear pieces using "bias". It gives different probabilities of activating the neural network or not. This is very useful in the case of Cryptanalysis. Two names are used to design the same domain of research: Neuro-Cryptography and Neural Cryptography.

3.4.1 Neural key exchange protocol

The most used protocol for key exchange between two parties A and B in the practice is DiffieHellman key exchange protocol. Neural key exchange, which is based on the synchronization of two tree parity machines, should be a secure replacement for this method. Synchronizing these two machines is similar to synchronizing two chaotic oscillators in chaos communications.

Each party (A and B) uses its own **tree parity machine.** The tree parity machine is a special type of multi-layer feedforward neural network. Synchronization of the tree parity machines is achieved in these steps

1. Initialize random weight values
2. Execute these steps until the full synchronization is achieved
   (a) Generate random input vector X
   (b) Compute the values of the hidden neurons
   (c) Compute the value of the output neuron
   (d) Compare the values of both tree parity machines
      i. Outputs are the same: go to 2(a)
      ii. Outputs are different: one of the suitable learning rules is applied to the weights

The following **Hebbian learning rule** can be used for the synchronization

$$w_i^+ = g(w_i + \sigma_i x_i \Theta(\sigma_i \tau)\Theta(\tau^A \tau^B))$$

After the full synchronization is achieved (the weights w_{ij} of both tree parity machines are same), A and B can use their weights as keys. This method is known as a bidirectional learning. [3]

The synchronized weights are used to construct an ephemeral key exchange protocol for a secure transmission of secret data. It is shown that an opponent who knows the protocol and all details of any transmission of the data has no chance to decrypt the secret message, since tracking the weights is a hard problem compared to synchronization [3]. The complexity of the generation of the secure channel is linear with the size of the network.

4 Adversarial Neural Cryptography

This section discusses how to protect the confidentiality of plaintexts using shared keys. It describes the organization of the system that we consider, and the objectives of the participants in this system. It also explains the training of these participants, defines their architecture, and presents experiments.

A classic scenario in security involves three parties: Alice, Bob, and Eve. Typically, Alice and Bob wish to communicate securely, and Eve wishes to eavesdrop on their communications. Thus, the desired security property is secrecy (not integrity), and the adversary is a passive attacker that can intercept communications but that is otherwise quite limited: it cannot initiate sessions, inject messages, or modify messages in transit.

4.1 The ANC Model

We start with a particularly simple instance of this scenario, depicted in figure 4, in which Alice wishes to send a single confidential message P to Bob. The message P is an input to Alice. When Alice processes this input, it produces an output C. (P stands for plaintext and C stands for ciphertext). Both Bob and Eve receive C, process it, and attempt to recover P. We represent what they compute by P_{Bob} and P_{Eve}, respectively.

Alice and Bob have an advantage over Eve: they share a secret key K [2]. We treat K as an additional input to Alice and Bob. We assume one fresh key K per plaintext P, but, at least at this abstract level, we do not impose that K and P have the same length.

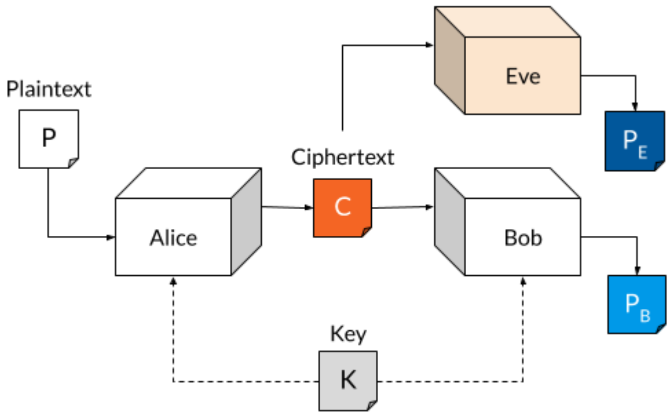

Figure 4: The ANC Model proposed by Abadi et al.

For us, Alice, Bob, and Eve are all neural networks. We describe their structures in Section 4.1.3. They each have parameters, which we write Φ_A, Φ_B, and Φ_E, respectively. Since Φ_A and Φ_B need not be equal, encryption and decryption need not be the same function even if Alice and Bob have the same structure. As is common for neural networks, Alice, Bob, and Eve work over tuples of floating-point numbers, rather than sequences of bits. In other words, K, P, PBob, PEve, and C are all tuples of floating-point numbers. Note that, with this formulation, C, P_{Bob}, and P_{Eve} may consist of arbitrary floating-point numbers even if P and K consist of 0s and 1s.

This set-up, although rudimentary, suffices for basic schemes, in particular allowing for the possibility that Alice and Bob decide to rely on K as a one-time pad, performing encryption and decryption simply by XORing the key K with the plaintext P and the ciphertext C, respectively. However, we do not require that Alice and Bob function in this wayand indeed, in our experiments in Section 2.5, they discover other schemes. For simplicity, we ignore the process of generating a key from a seed. We also omit the use of randomness for probabilistic encryption. Such enhancements may be the subject of further work.

4.1.1 Objectives of the Participants

Informally, the objectives of the participants are as follows. Eves goal is simple: to reconstruct P accurately (in other words, to minimize the error between P and P_{Eve}). Alice and Bob want to communicate clearly (to minimize the error between P and PBob), but also to hide their communication from Eve. Note that, in line with modern cryptographic definitions (Goldwasser & Micali, 1984), we do not require that the ciphertext C look random to Eve. A ciphertext may even contain obvious metadata that identifies it as such. Therefore, it is not a goal for Eve to distinguish C from a random value drawn from some distribution. In this respect, Eves objectives contrast with common ones for the adversaries of GANs. On the other hand, one could try to reformulate Eves goal in terms of distinguishing the ciphertexts constructed from two different plaintexts.

Much as in the definitions of GANs, we would like Alice and Bob to defeat the best possible version of Eve, rather than a fixed Eve. Of course, Alice and Bob may not win for every plaintext and every key, since knowledge of some particular plaintexts and keys may be hardwired into Eve. (For instance, Eve could always output the same plaintext, and be right at least once.) Therefore, we assume a distribution on plaintexts and keys, and phrase our goals for Alice and Bob in terms of expected values.

4.1.2 Mathematical Background

We write $A(\Phi_A, P, K)$ for Alices output on input P, K, write $B(\Phi_B, C, K)$ for Bobs output on input C, K, and write $E(\Phi_E, C)$ for Eves output on input C. We introduce a distance function d on plaintexts.

Although the exact choice of this function is probably not crucial, for concreteness we take the L1 distance

$$d(P, P') = \Sigma_{i=1}^{N} |P_i - P'_i|$$

where N is the length of plaintexts. We define a per-example loss function for Eve. Intuitively this represents how much Eve is wrong when the plaintext is P and the key is K. We also define a loss function for Eve over the distribution on plaintexts and keys by taking an expected value:

$$L_E(\Phi_A, \Phi_E) = \mathbb{E}_{P,K}[d(P, E(\Phi_E, A(\Phi_A, P, K)))]$$

We obtain the optimal Eve by minimizing this loss:

$$O_E(\theta_A) = argmin_{\theta_E}(L_E(\theta_A, \theta_E))$$

Similarly, we define a per-example reconstruction error for Bob, and extend it to the distribution on plaintexts and keys. We define a loss function for Alice and Bob by combining L_B and the optimal value of L_E:

$$L_{AB}(\Phi_A, \Phi_E) = L_B(\Phi_A, \Phi_B) - L_E(\Phi_A, O_E(\theta_A))$$

This combination reflects that Alice and Bob want to minimize Bobs reconstruction error and to maximize the reconstruction error of the optimal Eve. The use of a simple subtraction is somewhat arbitrary; below we describe useful variants. We obtain the optimal Alice and Bob by minimizing

$$(O_A, O_B) = argmin_{(\theta_A, \theta_B)}(L_{AB}(\theta_A, \theta_B))$$

We write optimal in quotes because there need be no single global minimum. In general, there are many equi-optimal solutions for Alice and Bob. As a simple example, assuming that the key is of the same size as the plaintext and the ciphertext, Alice and Bob may XOR the plaintext and the ciphertext, respectively, with any permutation of the key, and all permutations are equally good as long as Alice and Bob use the same one; moreover, with the way we architect our networks (see Section 2.4), all permutations are equally likely to arise.

4.1.3 Network Architecture

The Architecture of Alice, Bob, and Eve Because we wish to explore whether a general neural network can learn to communicate securely, rather than to engineer a particular method, we aimed to create a neural network architecture that was sufficient to learn mixing functions such as XOR, but that did not strongly encode the form of any particular algorithm. To this end, we chose the following mix & transform architecture. It has a first fully-connected (FC) layer, where the number of outputs is equal to the number of inputs. The plaintext and key bits are fed into this FC layer. Because each output bit can be a linear combination of all of the input bits, this layer enablesbut does not mandatemixing between the key and the plaintext bits. In particular, this layer can permute the bits.

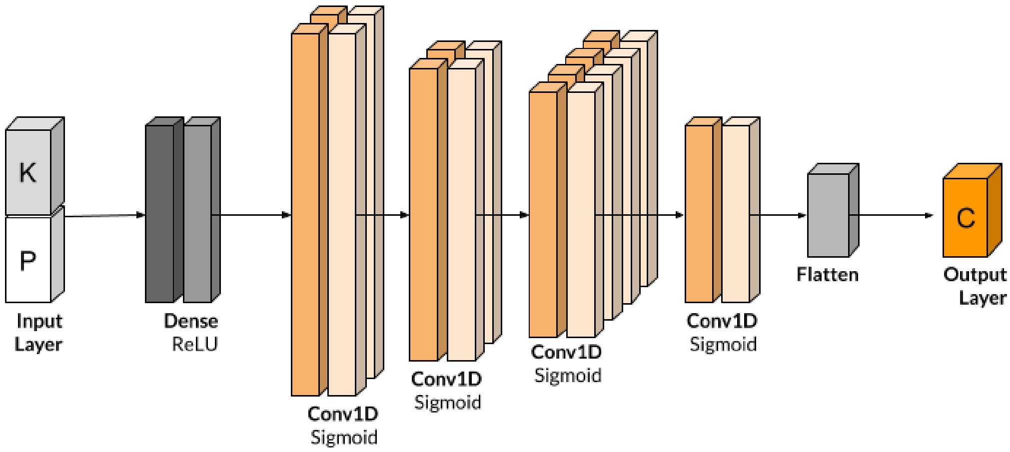

Figure 5: Modified network Model from Abadi et al.

The FC layer is followed by a sequence of convolutional layers, the last of which produces an output of a size suitable for a plaintext or ciphertext. These convolutional layers learn to apply some function to groups of the bits mixed by the previous layer, without an a priori specification of what that function should be. Notably, the opposite order (convolutional followed by FC) is much more common in image-processing applications. Neural networks developed for those applications frequently use convolutions to take advantage of spatial locality.

For neural cryptography, we specifically wanted localityi.e., which bits to combineto be a learned property, instead of a pre-specified one. While it would certainly work to manually pair each input plaintext bit with a corresponding key bit, we felt that doing so would be uninteresting. We refrain from imposing further constraints that would simplify the problem. For example, we do not tie the parameters Φ_A and Φ_B, as we would if we had in mind that Alice and Bob should both learn the same function, such as XOR.

4.2 The Cryptonet Model

In this section, we describe a proposed improvement to the ANC methodology using the Chosen-Plaintext Attack (CPA) called the CPA-ANC. Additionally, we present a simple NN capable of learning the One-Time Pad which will be used to test this new methodology against the traditional ANC.

4.2.1 Chosen-Plaintext Attack

As we will see in the experiments of Section 5, the problem with the approach proposed in the original ANC work [6] is that **Eve's job is too hard.**

It must decrypt a random message having access only to the ciphertext. The consequence is that, under this methodology, Alice and Bob learn to communicate with cryptosystems that are not truly secure. Therefore, one can conclude that Alice and Bob do not have to do much effort to protect themselves against Eve, leading in insecure cryptosystems. It is possible to improve ANC considering a more robust model of security for Alice, Bob and Eve. Namely, we will let Eve to mount a CPA. Therefore, to be protected against Eve, Alice and Bob will have to find a system secure against the CPA.

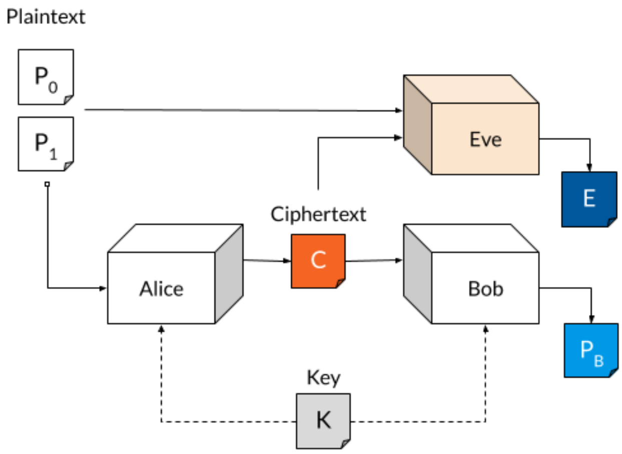

Figure 6: The Cryptonet Model proposed by Coutinho et al.

In this new setup Eve will choose two messages P_0 and P_1 and send them to Alice. Alice will choose one of these messages randomly, encrypt it with the NN obtaining the ciphertext C and send it to Eve and Bob. As usual, Bob will decrypt the message with a NN. However, Eve will not try to decrypt C, but will only output 0 if it believes P_0 was encrypted or 1 if it believes P_1 was encrypted. We call this the CPA-ANC setup and it is illustrated in Figure 6.

4.2.2 Network Architecture

We are building a NN complex enough to be able to learn some form of cryptography but simple enough to allow us to reason about its security. To do this, we used a continuous generalization for the operator XOR, which is a well-known binary and non-differentiable operation that happens to be used a lot in cryptography. [6]

Thus, if we want a NN that can perform the XOR operation internally, we need a generalization of the operation. It is possible to generalize the XOR operation using the unit circle by mapping the bit 0 to the angle 0 and the bit 1 to the angle π. In this way, the XOR is equivalent to the sum of the angles.

Thus, it is possible to work with angles different from 0 or p, generalizing bits to a continuous space. The following equation defines the mapping of a bit b into an angle:

$$f(b) = \arccos(1 - 2b)$$

The inverse of f provides the mapping of an angle a to a continuous bit:

$$f^{-1}(a) = \frac{1 - \cos(a)}{2}$$

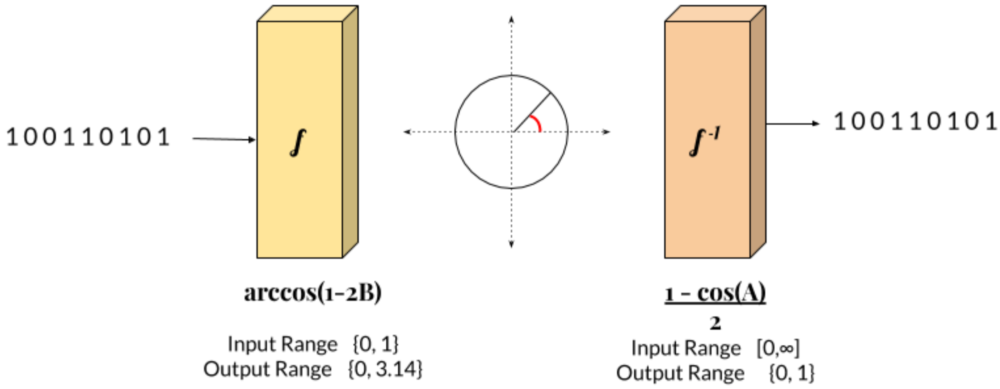

Figure 7: Transformation Function in Cryptonet

Basically, CryptoNet receives as input the plaintext and the key and, for each bit received, applies the transformation $f(b)$, resulting in angles. The next step is a standard matrix multiplication followed by the inverse transformation $f^{-1}(a)$ resulting in the ciphertext. Note that the ciphertext is not composed of bits but by floating number between 0 and 1.

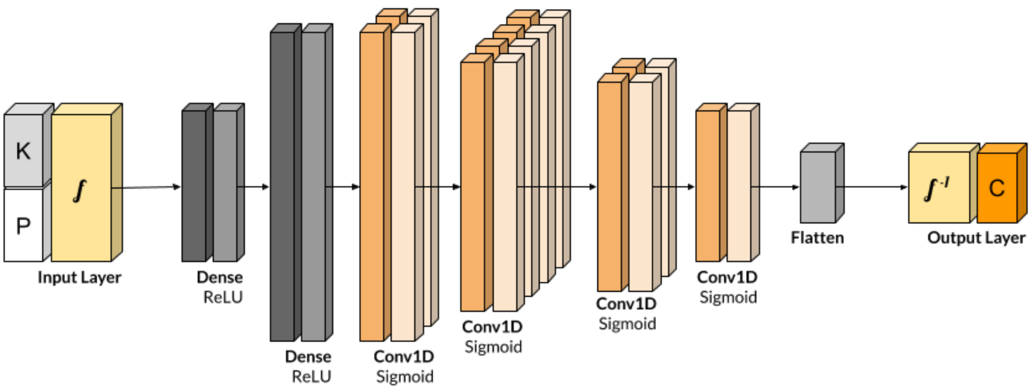

Figure 8: Modified network Model from Coutinho et al.

The realized network model is a hybrid of the two systems considered above. It contains the convolutional layers from the original ANC model and applies the transform function and CPA over the top. This is done for reasons of convergence and complexity. The original model proposed by Coutinho et al, is a very simple multilayer perceptron and does not hold up to large amounts of data. This modified setup helps us incorporate the good things from both the versions to produce a better result.

5 Implementation

The implementation of this project was done entirely in **Python 3.6** using some popular deep learning libraries and tools to make the work easier. Python was chosen over other languages like MATLAB and R since the code is very versatile and relies on open-source software. Python is also the language of choice for deployment of ML models in production and is thus ideal.

The libraries used in this project for the implementation of the network models are

- **PyTorch 1.6**; a popular library for functional ML models
- **Tensorboard**; for visualizations and tracking the training progress
- **MatPlotLib**; for plotting charts and figures

Other than these other libraries are used as and when necessary in the code. Further, we will attempt to use the work of Hao Li et al [7] to plot the loss landscape of the high dimensional space of the networks. Other research based software like DeepVis [8] is also used.

5.1 Methodology

The models that are written were first tested to produce what we call a **successful communication**. This means that we run the network without the involvement of an eavesdropper (Eve) and try to get Alice and Bob to communicate successfully. This has the effect of synchronizing the two networks.

We produce a random string of bits as plaintext and use a predetermined key of the same length. These are then concatenated to form the input to the encrypting networks.

```
# We use the generator syntax for lists
KEY = [random.randint(0, 1) for i in range(BLOCKSIZE)]
PLAIN = [[random.randint(0, 1) for x in range(BLOCKSIZE)]
  for i in range(BATCHLEN)]

# ...
for P in PLAIN:
  P = torch.Tensor(P)
  K = torch.Tensor(KEY)

  torch.cat([P, K], dim=0)
```

After we have trained the networks for a few epochs without the adversary, we look at the graph of the loss plotted over the training batches and a **reduction in loss will mean** that the communication is successful.

We then introduce the eavesdropper to the mix and let the networks retrain with it. This has the effect of changing the communication scheme learnt by the networks into something more secure. Alice is directly affected by the loss of Eve and the better Eve is at predicting the original plaintext, the harder Alice has to work to develop a secure cryptosystem.

```
# We choose the L1 loss initially
lossfn = nn.L1Loss()

bob_reconst_loss = lossfn(Pb, P)
eve_reconst_loss = lossfn(Pe, P)

# Linear loss
alice_loss = bob_reconst_loss - eve_reconst_loss
```

This system is trained for the remaining epochs and is then tested for its convergence by studying it's loss trend over time.

5.2 Structure of the Network

We have two main structures of network that we have implemented and experimented with. These are the original ANC model proposed by Abadi et al [2] and the second is a hybrid model of the improvement proposed by Coutinho et al [6]. This was motivated by poor results with the original model proposed and the ambiguity about the network architecture used by the team.

5.2.1 ANC Model

The model architecture is as described in section 4.1.3.

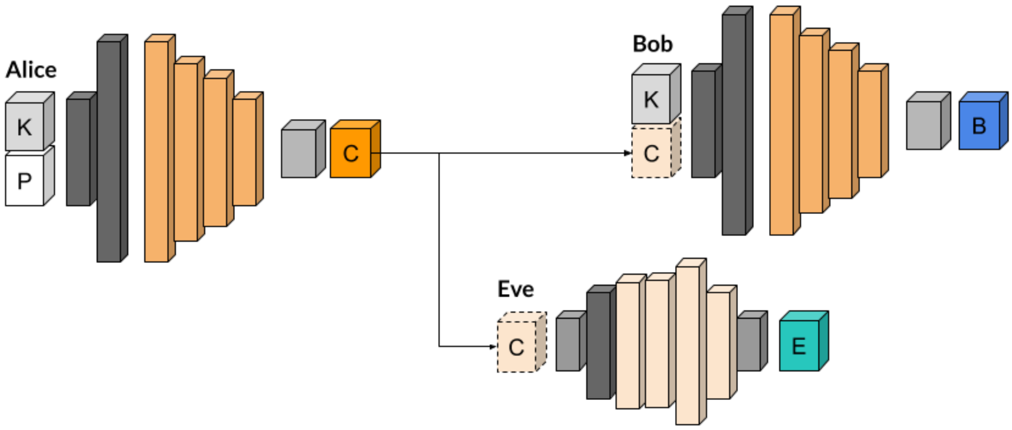

Figure 9: Network Structure for ANC

```
class KeyholderNetwork(nn.Module):
  def __init__(self, blocksize):
    super(KeyholderNetwork, self).__init__()

    self.blocksize = blocksize
    self.entry = nn.Identity(blocksize * 2)

    self.fc1 = nn.Linear(in_features=blocksize * 2, out_features=blocksize * 2)

    self.conv1 = nn.Conv1d(in_c=1, out_c=2, kernel_size=4, stride=1)
    self.conv2 = nn.Conv1d(in_c=2, out_c=2, kernel_size=2, stride=2)
    self.conv3 = nn.Conv1d(in_c=2, out_c=4, kernel_size=1, stride=1)
    self.conv4 = nn.Conv1d(in_c=4, out_c=1, kernel_size=1, stride=1)

  def forward(self, inputs):
    inputs = self.entry(inputs)
    inputs = torch.sigmoid(self.fc1(inputs))

    inputs = inputs.unsqueeze(0).unsqueeze(0)

    inputs = torch.sigmoid(self.conv1(inputs))
    inputs = torch.sigmoid(self.conv2(inputs))
    inputs = torch.sigmoid(self.conv3(inputs))

    inputs = F.hardsigmoid(self.conv4(inputs))

    return inputs.view(self.blocksize)
```

The last layer of the model was converted to a **hardsigmoid** layer. This works almost like the sigmoid function but better approximates a discrete output.

The plaintext and key are converted to PyTorch Tensors which are then concatenated and sent to the encrypting networks. For ease of use, the networks that use the key are instances of a **KeyholderNetwork** class which takes two **BLOCKSIZE** length inputs. This allows Alice and Bob to have the same architecture.

```
alice = KeyholderNetwork(BLOCKSIZE)
bob = KeyholderNetwork(BLOCKSIZE)
eve = AttackerNetwork(BLOCKSIZE)

lossfn = nn.L1Loss()

opt_alice_bob = optim.Adam(alice.parameters() + bob.parameters(), lr=0.0008)
opt_eve = optim.Adam(eve.parameters(), lr=0.0008)

for E in range(BATCHES):
  for P in PLAIN:
    P = torch.Tensor(P)
    K = torch.Tensor(KEY)

    cipher = alice(torch.cat([P, K], dim=0))
    cipher.detach()

    Pb = bob(torch.cat([cipher, K], dim=0))
    Pe = eve(cipher)

    bob_reconst_loss = lossfn(Pb, P)
    eve_reconst_loss = lossfn(Pe, P)

    # Linear loss
    alice_loss = (BETA * bob_reconst_loss) - (GAMMA * eve_reconst_loss)

    bob_reconst_loss.backward(retain_graph=True)
    eve_reconst_loss.backward(retain_graph=True)
    alice_loss.backward(retain_graph=True)

    opt_alice_bob.step()
    opt_eve.step()

    delta_alice = alice_running_loss[-1] - alice_loss.item()
    delta_bob = bob_running_loss[-1] - bob_reconst_loss.item()
    delta_eve = eve_running_loss[-1] - eve_reconst_loss.item()

    # Stop when no/low avg change
    if ((delta_alice + delta_bob + delta_eve)/3 <= 0.00005):
      print('--- Training Stalled ---')
      break

  print(f'Finished Batch {E}')
  recalc_plain()

print('Finished Training')
```

5.2.2 Cryptonet Model

This network has almost the same architecture as the ANC model, but has a few changes. The inputs go through a functional transform layer which converts the bits into angles [6].

The layer sizes have been changed by experimental inference and have been found to work better in the configuration illustrated in the figure 8.

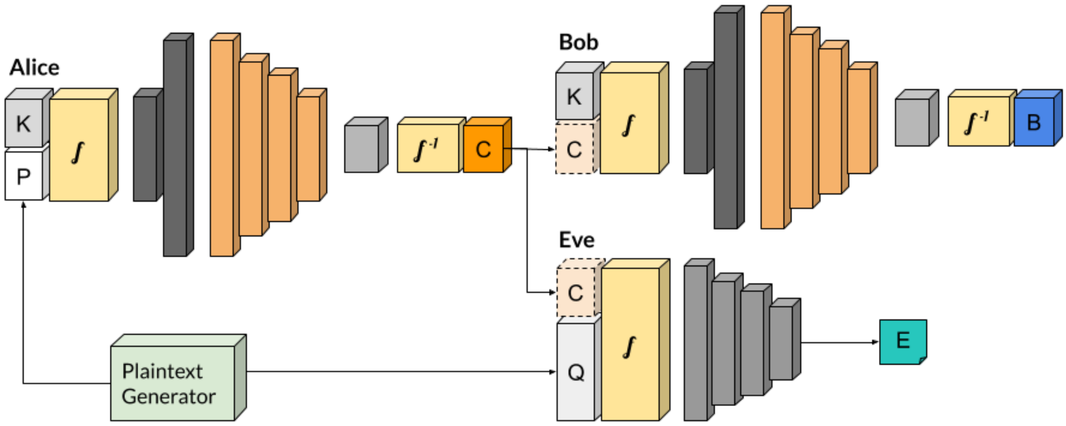

Figure 10: Network Structure for Cryptonet

```python
class KeyholderNetwork(nn.Module):
  def __init__(self, blocksize):
    super(KeyholderNetwork, self).__init__()
    self.entry = nn.Identity(blocksize * 2)

    self.fc1 = nn.Linear(in_features=blocksize * 2, out_features=blocksize * 4)
    self.fc2 = nn.Linear(in_features=blocksize * 4, out_features=blocksize * 2)
    self.fc3 = nn.Linear(in_features=blocksize, out_features=blocksize)

    # ... Same conv layers as in ANC

  def forward(self, inputs):
    inputs = self.entry(inputs)
    inputs = torch.acos(1 - torch.mul(inputs, 2))

    inputs = torch.relu(self.fc1(inputs))
    inputs = torch.relu(self.fc2(inputs))

    inputs = inputs.unsqueeze(dim=0).unsqueeze(dim=0)

    inputs = torch.sigmoid(self.conv1(inputs))
    inputs = torch.sigmoid(self.conv2(inputs))
    inputs = torch.sigmoid(self.conv3(inputs))
    inputs = torch.sigmoid(self.conv4(inputs))

    inputs = inputs.view(self.blocksize)
    inputs = torch.relu(self.fc3(inputs))

    inputs = torch.div(1 - torch.cos(inputs), 2)
    inputs = F.hardsigmoid(torch.mul(inputs, 10) - 5)

    return inputs
```

Similar to the ANC model, the inputs are concatenated before being sent to Alice. However, the plaintext is randomly chosen from one of two pre-generated plaintexts. Eve is given both the plaintexts and the ciphertext and has to determine if the cipher was produced either from P_0 or P_1. Its output is a probability between 0 and 1.

Here we also train the model for half of the epoch without the involvement of Eve, i.e. not training Eve and not backpropagating its loss, while for the other half we have Eve in the system.

It was also noted from experimentation that the **Mean Squared Error Loss (L2 Loss)** works better in this scenario. We also experimented with **Binary Crossentropy Loss** but without significantly better results.

```
# Initialize Networks
alice = KeyholderNetwork(BLOCKSIZE)
bob = KeyholderNetwork(BLOCKSIZE)
eve = AttackerNetwork(BLOCKSIZE)

dist = nn.MSELoss()
# dist = nn.BCELoss()

ab_params = itertools.chain(alice.parameters(), bob.parameters())
opt_alice_bob = torch.optim.Adam(ab_params, lr=1e-3, weight_decay=1e-5)

opt_eve = torch.optim.Adam(eve.parameters(), lr=2e-4)

# Training loop
torch.autograd.set_detect_anomaly(True)

for E in range(EPOCHS):
  print(f'Epoch {E + 1}/{EPOCHS}')
  K = torch.Tensor(KEY)

  for B in range(BATCHES):
    for X in PLAIN:
      P0 = torch.Tensor(X[0])
      P1 = torch.Tensor(X[1])

      R = random.randint(0, 1)
      P = torch.Tensor(X[R])

      C = alice(torch.cat([P, K], dim=0))
      Pb = bob(torch.cat([C, K], dim=0))

      # Loss and BackProp
      bob_dec_loss = dist(Pb, P)
      opt_alice_bob.zero_grad()

      if B > BATCHES/2:
        Re = eve(torch.cat([P0, P1, C.detach()], dim=0))
        eve_adv_loss = dist(Re, torch.Tensor([1 - R, R]))
        bob_dec_loss = dist(Pb, P) + torch.square(1 - eve_adv_loss)

        bob_dec_loss.backward(retain_graph=True)
        opt_alice_bob.step()

        opt_eve.zero_grad()
        eve_adv_loss.backward(retain_graph=True)
        opt_eve.step()
      else:
        bob_dec_loss.backward(retain_graph=True)
        opt_alice_bob.step()
```

5.3 Training

The training for this network is accomplished, as stated before, by first training without the eavesdropper so that the communication can be established. This ensures that the Alice and Bob neural networks are synchronized before introducing Eve. After a few epochs, we introduce Eve to the system and let the training complete, which watching the training loss.

We have used the **Adam Optimizer** which handles the backpropagation steps in the training of the networks. The Adam optimization algorithm is an extension to stochastic gradient descent that has recently seen broader adoption for deep learning applications in computer vision and natural language processing. Instead of adapting the parameter learning rates based on the average first moment (the mean) as in RMSProp, Adam also makes use of the average of the second moments of the gradients (the uncentered variance).

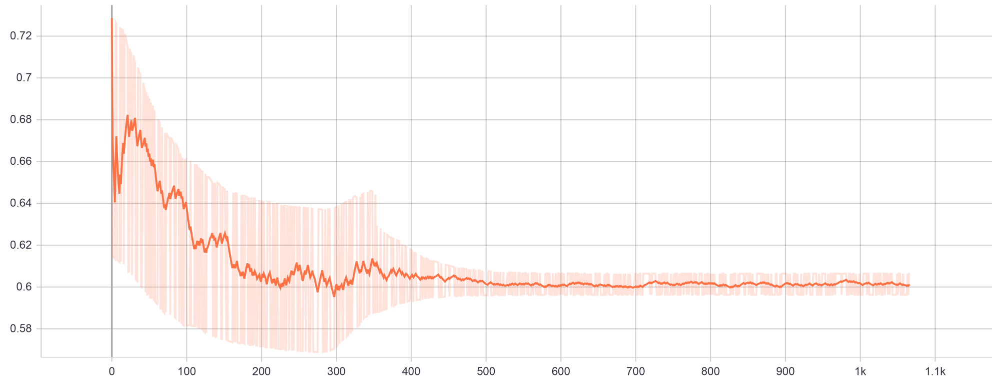

Figure 11: Training Loss Trend with Cryptonet

The loss while training is recorded using Tensorboard and this helps us keep an eye on the gradients and allows us to detect a stalled training and stop.

5.3.1 Training Parameters

The parameters which aren't learnt by the network but directly affect the performance are called **hyperparameters**. These are important since the right choice of hyperparameters can get us to the optimal model very quickly.

For our purposes the important parameters are the **key length, learning rate and the loss coefficients** in calculation of the loss for Alice and Bob. Various combinations are tried until one good set of values is obtained by experimentation.

The following table lists the various values of the hyperparameters that were tried and produced some useful results.

Key Size	**Learning Rate**	**Weight Decay**
4 bits	0.0002	0.000001
8 bits	0.0004	0.000002
16 bits	0.0008	
32 bits		

5.3.2 Problems in Training

One of the most common problems with training Generative Adversarial Networks is that that they do not always converge. Given the network parameters and the associated hyperparameters, there may or may not be a common solution in the solution-space of the networks. Thus the adversarial training does not always lead to a decreasing loss.

6 Results

After training the networks suitably, they are put through the validation procedure to test their efficacy with unseen new data. The models that meet a reasonable level of validation accuracy are considered to have converged and thus a success.

The following figures show the loss trends for the ANC model with and without the adversary. We can see the loss decreasing fast without the adversary but when the eavesdropper is introduced, the loss still decreases. This is a sign that the cryptosystem is working.

However the rate of change of loss does not decrease, indicating that the Eve isnt affecting Alice and Bob a lot. This is because its job is too difficult [6].

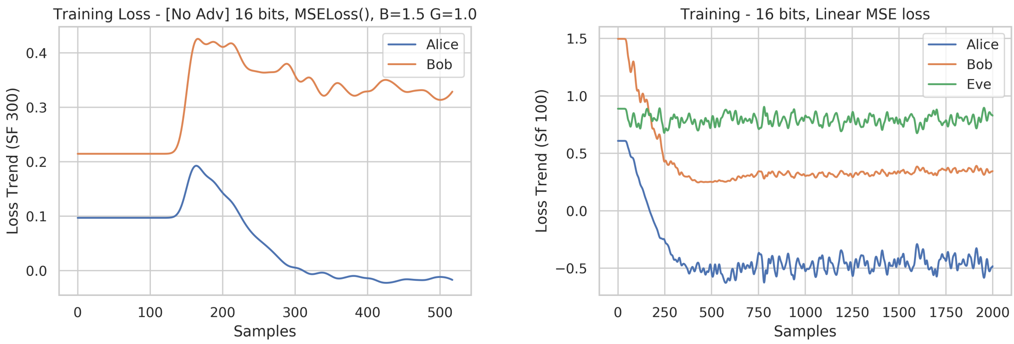

Figure 12: Loss Trend with ANC model by Abadi et al.

Key Size	Learning Rate	Epochs	Convergence
8 bits	0.0008	8	4/10
16 bits	0.0008	10	4/10
16 bits	0.0010	16	6/10

The table above shows the number of times out of 10, that the networks converged with a reasonable validation accuracy with different hyperparameters in the training.

The following figures show the loss trends for the Cryptonet model with and without the adversary. Immediately we can notice that the rate of decrease of the loss is slower, which is a clear sign that the adversary Eve is having an effect on the training of Alice and Bob.

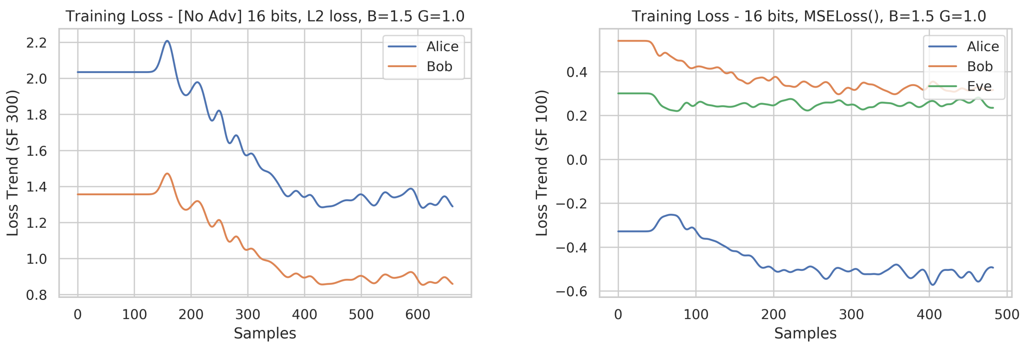

Figure 13: Loss Trend with Cryptonet model by Coutinho et al.

Key Size	Learning Rate	Epochs	Convergence
4 bits	0.0008	8	2/10
8 bits	0.0008	10	4/10
8 bits	0.0008	16	5/10

6.1 Conclusion

In this project, we demonstrate that neural networks can learn to protect communications. The learning does not require prescribing a particular set of cryptographic algorithms, nor indicating ways of applying these algorithms: it is based only on a secrecy specification represented by the training objectives. In this setting, we model attackers by neural networks; alternative models may perhaps be enabled by reinforcement learning.

There is more to cryptography than encryption. In this spirit, further work may consider other tasks, for example steganography, pseudorandom-number generation, or integrity checks. Finally, neural networks may be useful not only for cryptographic protections but also for attacks. While it seems improbable that neural networks would become great at cryptanalysis, they may be quite effective in making sense of metadata and in network traffic analysis.

6.2 Experimentation Areas

While this project had a reasonable level of success, there remains a lot of work to be done in this field. We will be examining the following areas of experimentation in the Major Project to take this further.

1. Using text embeddings and autoencoders in conjunction with these networks to produce human readable ciphers from ordinary text.
2. Investigating applications in end-to-end messaging and natural language to build high-grade word substitution ciphers.
3. Investigating the use of steganography in conjunction with an adversarial approach.

Bibliography

References

[1] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, “Generative adversarial nets,” in *Advances in neural information processing systems*, pp. 2672–2680, 2014.

[2] M. Abadi and D. G. Andersen, “Learning to protect communications with adversarial neural cryptography,” *arXiv preprint arXiv:1610.06918*, 2016.

[3] W. Kinzel and E. Kanter, “Secure exchange of information by synchronization of neural networks,” *Europhysics Letters (EPL) 57.1*, 2002.

[4] S. V. Goncharov, “Using fuzzy bits and neural networks to partially invert few rounds of some cryptographic hash functions,” 2019.

[5] B. Steven M., “Frank miller: Inventor of the one-time pad,” *Cryptologia*, vol. 35, no. 3, pp. 203–222, 2011.

[6] M. Coutinho, R. de Oliveira Albuquerque, F. Borges, L. J. Garcia Villalba, and T.-H. Kim, “Learning perfectly secure cryptography to protect communications with adversarial neural cryptography,” *Sensors*, vol. 18, no. 5, p. 1306, 2018.

[7] H. Li, Z. Xu, G. Taylor, C. Studer, and T. Goldstein, “Visualizing the loss landscape of neural nets,” 2018.

[8] J. Yosinski, J. Clune, A. Nguyen, T. Fuchs, and H. Lipson, “Understanding neural networks through deep visualization,” in *Deep Learning Workshop, International Conference on Machine Learning (ICML)*, 2015.

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