CS11-747 Neural Networks for NLP

Adversarial Methods

Graham Neubig

Carnegie Mellon University
Language Technologies Institute

Site
https://phontron.com/class/nn4nlp2020/

With many slides by Zihang Dai & Qizhe Xie

Generative Models

- Model a data distribution P(X) or a conditional one P(X|Y)

- Latent variable models: introduce another variable Z, and model $P(X) = \sum_{Z} P(X \mid Z) P(Z)$

A "Perfect" Generative Model Can

- Evaluate **likelihood**: $P(x)$

  - e.g. Perplexity in language modeling

- Generate **samples**: $x \sim P(X)$

  - e.g. Generate a sentence randomly from $P(X)$ or conditioned on some other information using $P(X|Y)$

- Infer **latent attributes**: $P(Z|X)$

  - e.g. Infer the "topic" of a sentence in topic models

No Generative Model is Perfect (so far)

	Non-Latent	VAE	GAN
Likelihood	☆☆☆☆	☆☆	☆
Generation (image)	☆☆☆	☆☆	☆☆☆☆
Inference		☆☆☆	☆☆

- Mostly rely on **MLE** (Lower bound) based training

- **GANs** are particularly good at **generating** continuous **samples**
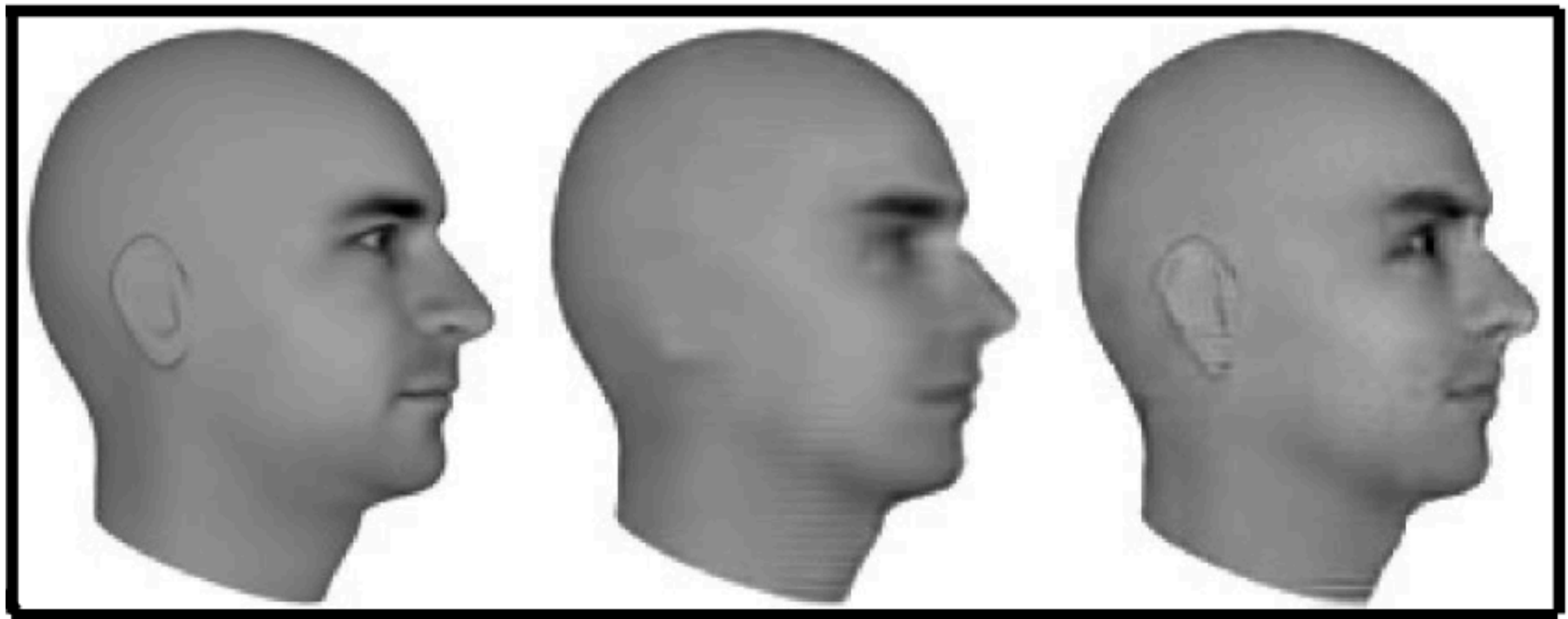
MLE vs. GAN

- Over-emphasis of common outputs, fuzziness

Real   MLE   Adversarial

- Note: this is probably a good idea if you are doing maximum likelihood!

Image Credit: Lotter et al. 2015

Adversarial Training

- Basic idea: create a "discriminator" that criticizes some aspect of the generated output

- **Generative adversarial networks:** criticize the generated output

- **Adversarial feature learning:** criticize the generated features to find some trait

Generative Adversarial Networks

Basic Paradigm

- Two models: generator and discriminator

  - **Discriminator:** given an image, try to tell whether it is real or not → P(image is real)

  - **Generator:** try to generate an image that fools the discriminator into answering "real"

- Desired result at convergence

  - Generator: generate perfect image

  - Discriminator: cannot tell the difference

Training Method
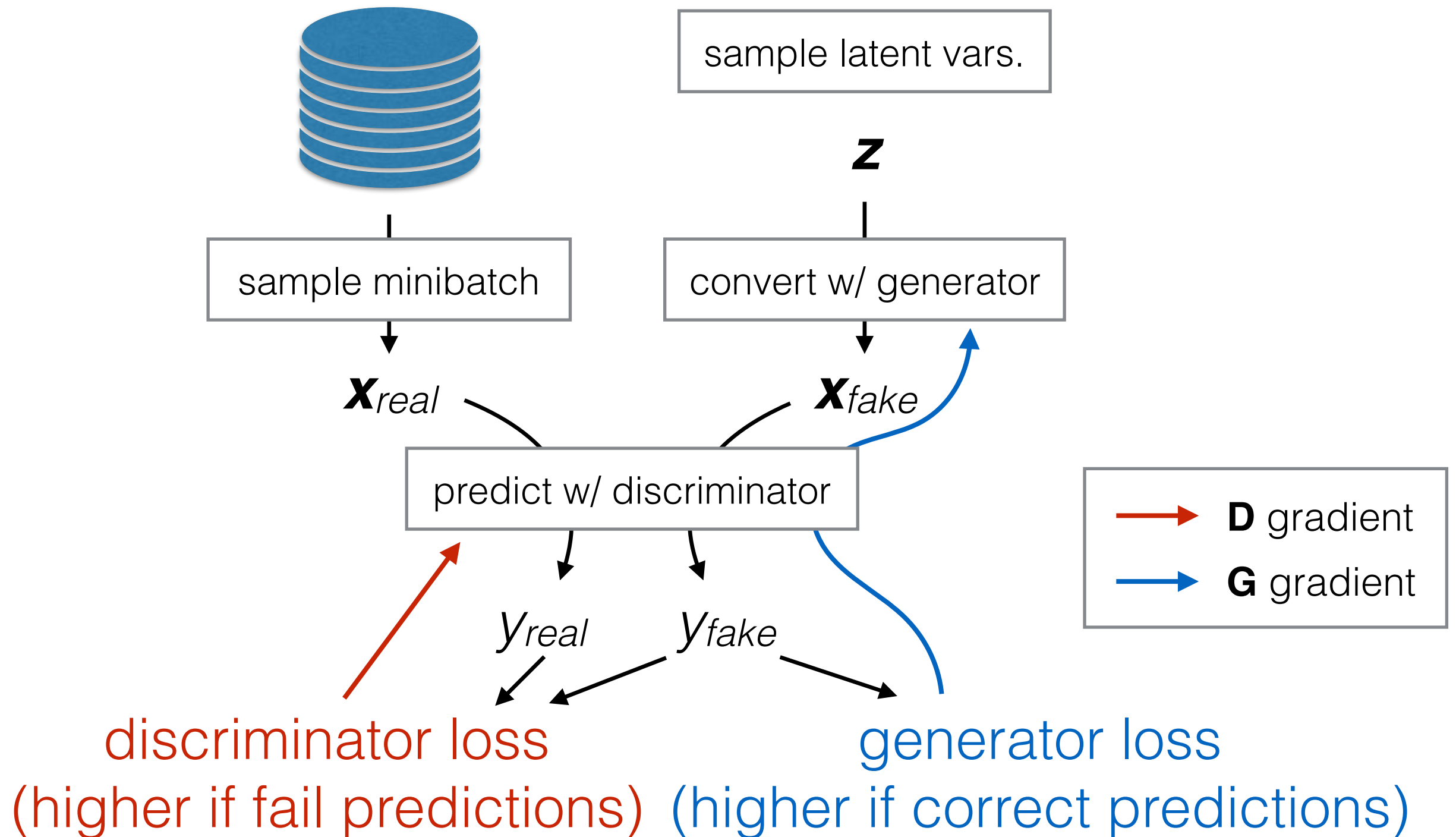
In Equations

- **Discriminator** loss function:

P(fake) = 1 - P(real)

$$\ell_D(\theta_D, \theta_G) = -\frac{1}{2}\mathbb{E}_{\boldsymbol{x} \sim P_{data}} \log D(\boldsymbol{x}) - \frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log(1 - D(G(\boldsymbol{z})))$$

Predict real for real data   Predict fake for fake data

- **Generator** loss function:

  - Make generated data **"less fake"** → Zero sum loss:

$$\ell_G(\theta_D, \theta_G) = -\ell_D(\theta_D, \theta_G)$$

  - Make generated data **"more real"** → Heuristic non-saturating loss:

$$\ell_G(\theta_D, \theta_G) = -\frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log D(G(\boldsymbol{z}))$$

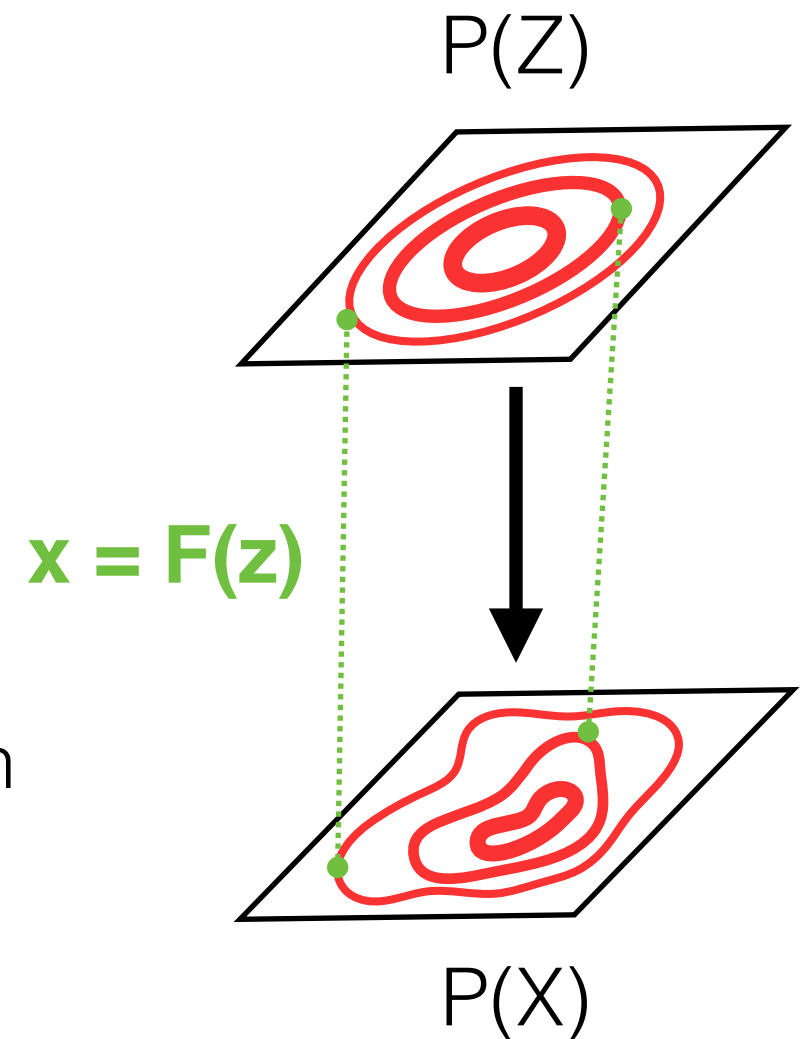 - **Latter** gives **better gradients** when discriminator accurate

Interpretation: Distribution Matching

Process

- [Step1] Z ~ P(Z), P(Z) can be any distribution

- [Step2] X = F(Z), F is a **deterministic** function

Result

- X is a random variable with a different distribution P(X), which decides by both P(Z) and F

- The process can produce any complicated distribution P(X) with a reasonable P(Z) and a powerful enough F

$$\tilde{z}_1 \qquad \tilde{z}_2 \qquad \tilde{z}_3 \qquad z_i \sim \text{Symbolic M}$$

$$z_i \sim \text{Symbolic M}$$

$$e_1 \qquad e_2 \qquad e_3$$

$$f_\phi(e)$$

$$x_1 \qquad x_2 \qquad x_3$$

$$e_i \sim \mathcal{N}(\boldsymbol{\mu}_{z_i}, \boldsymbol{\Sigma}_z)$$

$$e_i \sim P(Z) \boldsymbol{\mu}_{z_i}, \boldsymbol{\Sigma}_z$$

x = F(z)

$$x_i = f_\phi$$

$$x_i \sim \text{Point mass at } f_\phi$$

Symbolic Model

Neural Projector

In Pseudo-Code

- x_{real} ~ Training data

- z ~ $P(Z)$ $\rightarrow$ Normal(0, 1) or Uniform(-1, 1)

- $x_{fake} = \mathbf{G}(z)$

- $y_{real} = \mathbf{D}(x_{real})$ $\rightarrow$ $P(x_{real}$ is real)

- $y_{fake} = \mathbf{D}(x_{fake})$ $\rightarrow$ $P(x_{fake}$ is real)

- Train $\mathbf{D}$: $\min_D$ - log y_{real} - log (1 - y_{fake})

- Train $\mathbf{G}$: $\min_G$ - log y_{fake} $\rightarrow$ non-saturating loss

Why are GANs good?

- Discriminator is a **"learned metric"** parameterized by powerful neural networks

- Can easily pick up any kind of discrepancy, e.g. blurriness, global inconsistency

- Generator has **fine-grained** (gradient) signals to inform it what and how to improve

Problems in GAN Training

- GANs are great, but **training** is notoriously **difficult**

- Known problems

  - Convergence & Stability:

    - WGAN (Arjovsky et al., 2017)

    - Gradient-Based Regularization (Roth et al., 2017)

  - Mode collapse/dropping:

    - Mini-batch Discrimination (Salimans et al. 2016)

    - Unrolled GAN (Metz et al. 2016)

  - Overconfident discriminator:

    - One-side label smoothing (Salimans et al. 2016)

Applying GANs to Text

Applications of GAN Objectives to Language

- GANs for Language Generation (Yu et al. 2017)

- GANs for MT (Yang et al. 2017, Wu et al. 2017, Gu et al. 2017)

- GANs for Dialogue Generation (Li et al. 2016)

Problem! Can't Backprop through Sampling

sample latent vars.

$\boldsymbol{z}$

sample minibatch

convert w/ generator

$\boldsymbol{x}_{real}$

$\boldsymbol{x}_{fake}$

predict w/ discriminator

Discrete!
Can't backprop

y
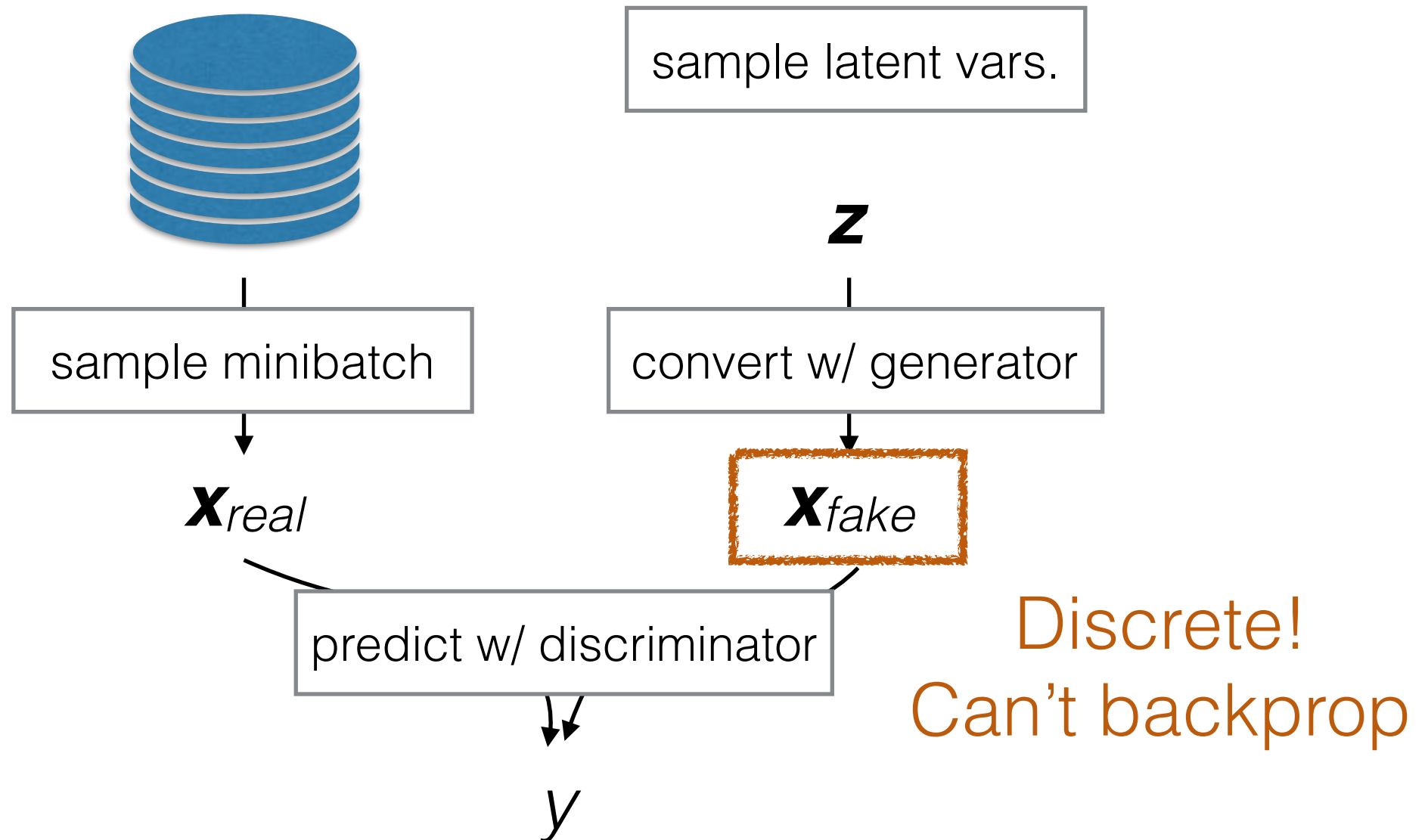
Solution: Use Learning Methods for Latent Variables

- Policy gradient reinforcement learning methods (e.g. Yu et al. 2016)

- Reparameterization trick for latent variables using Gumbel softmax (Gu et al. 2017)

Discriminators for Sequences

- Decide whether a particular generated output is true or not

- Commonly use CNNs as discriminators, either on sentences (e.g. Yu et al. 2017), or pairs of sentences (e.g. Wu et al. 2017)
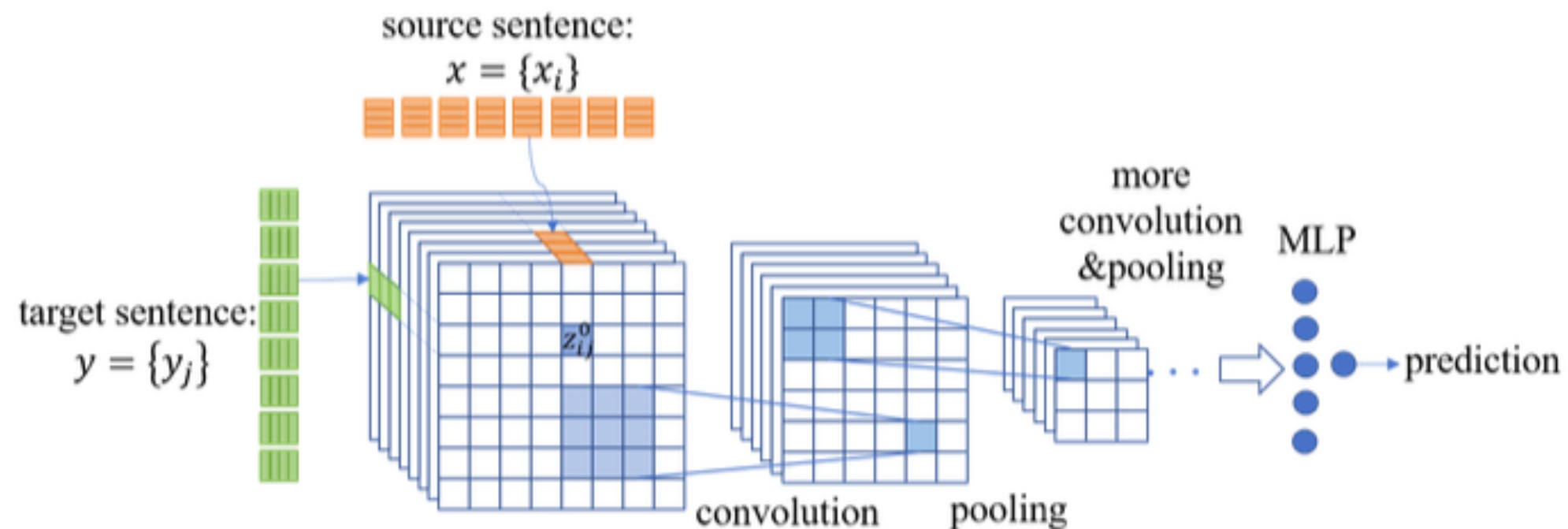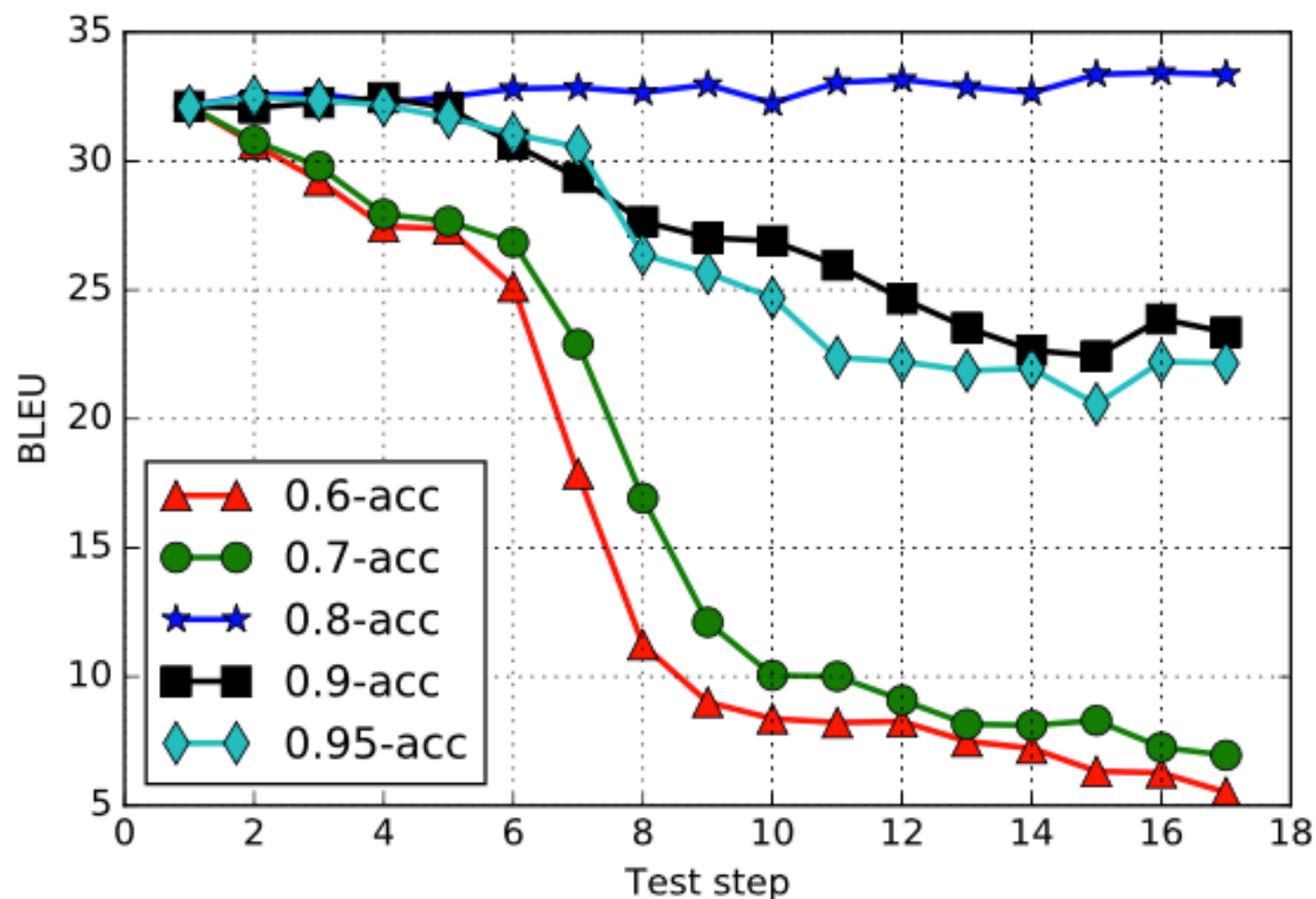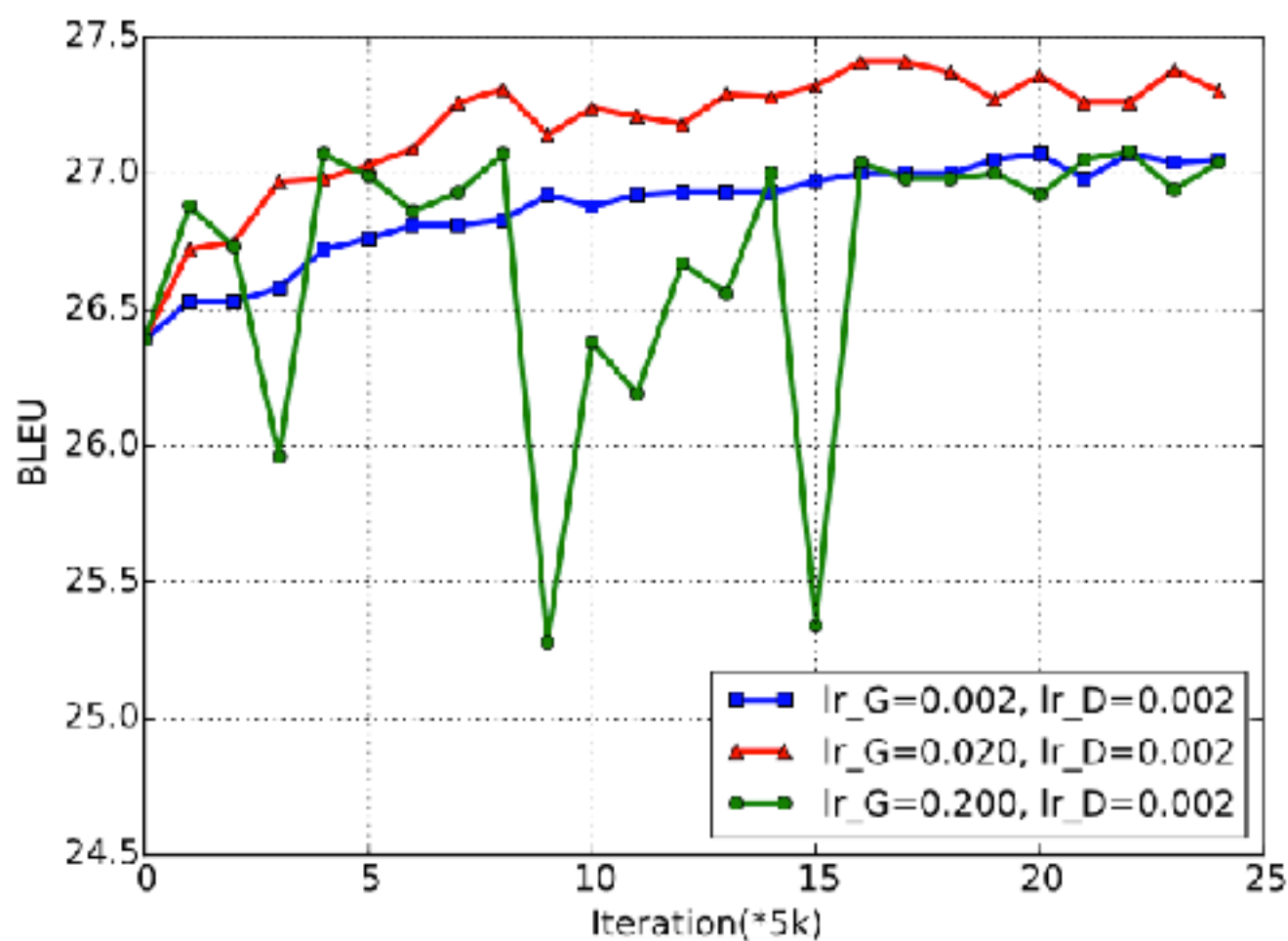
GANs for Text are Hard!
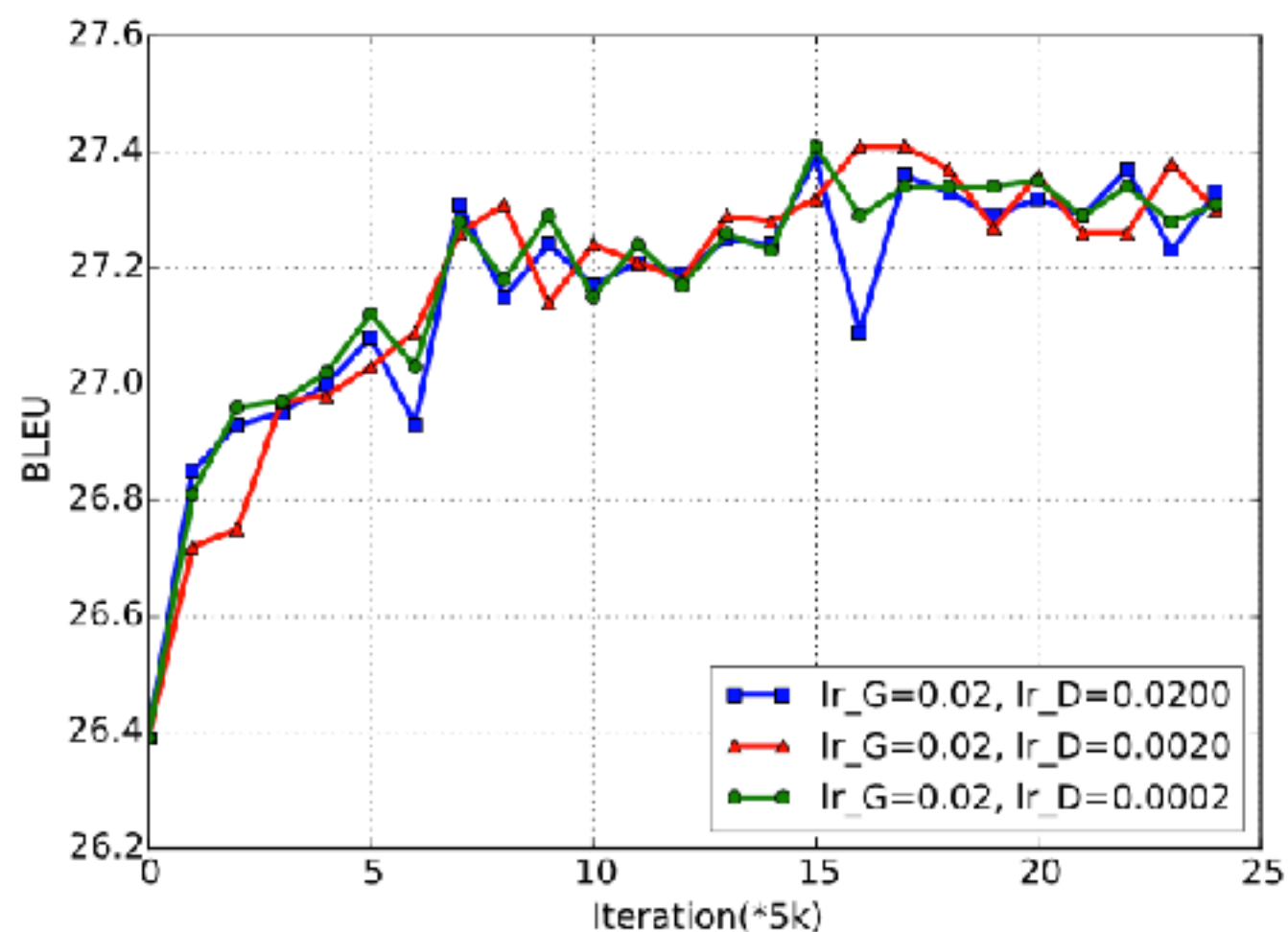## (Yang et al. 2017)

Type of Discriminator
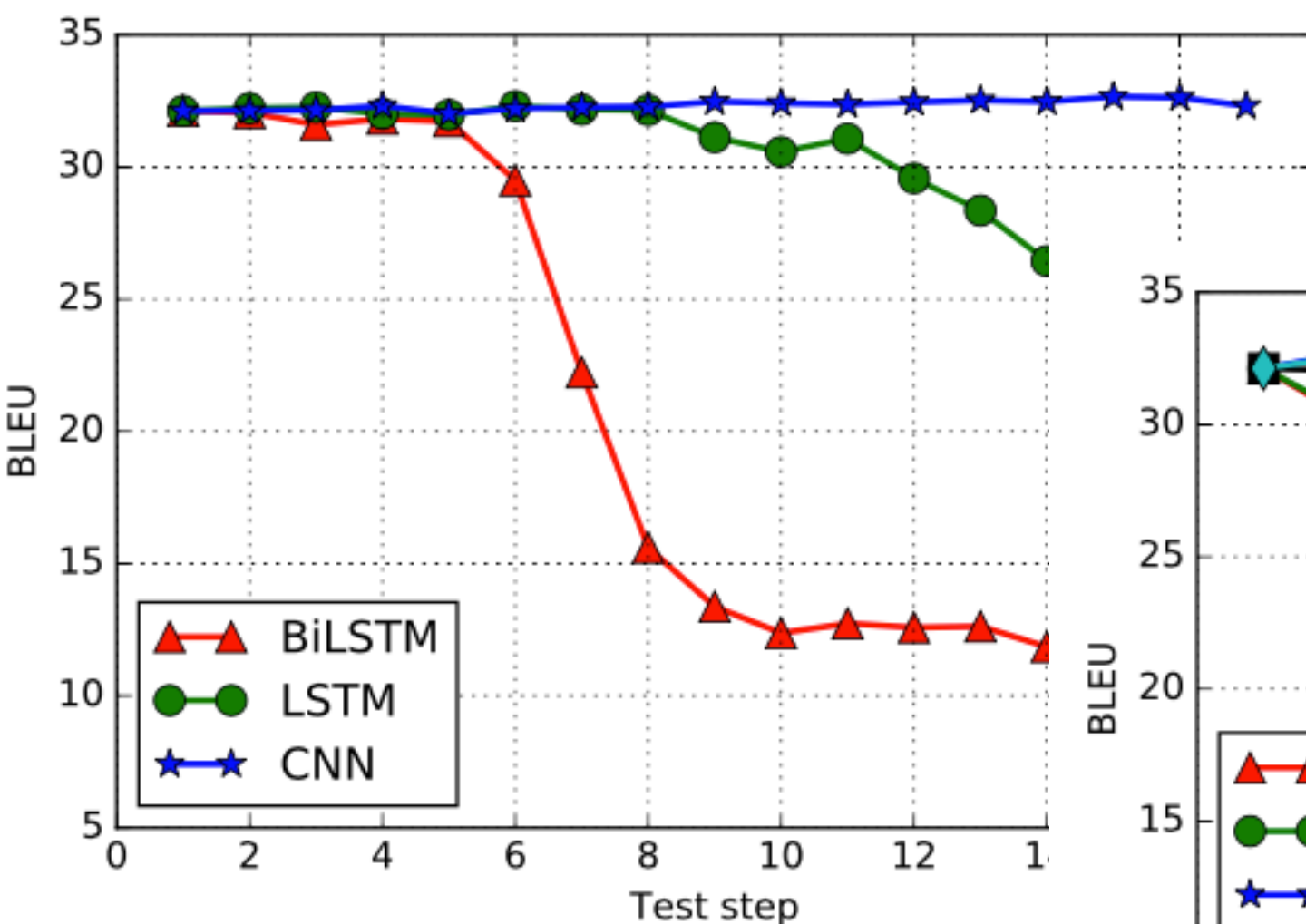
Strength of Discriminator

GANs for Text are Hard!
(Wu et al. 2017)

Learning Rate for Generator

Learning Rate for Discriminator

Stabilization Trick:
Assigning Reward to Specific Actions

- Getting a reward at the end of the sentence gives a credit assignment problem

- Solution: assign reward for partial sequences (Yu et al. 2016, Li et al. 2017)
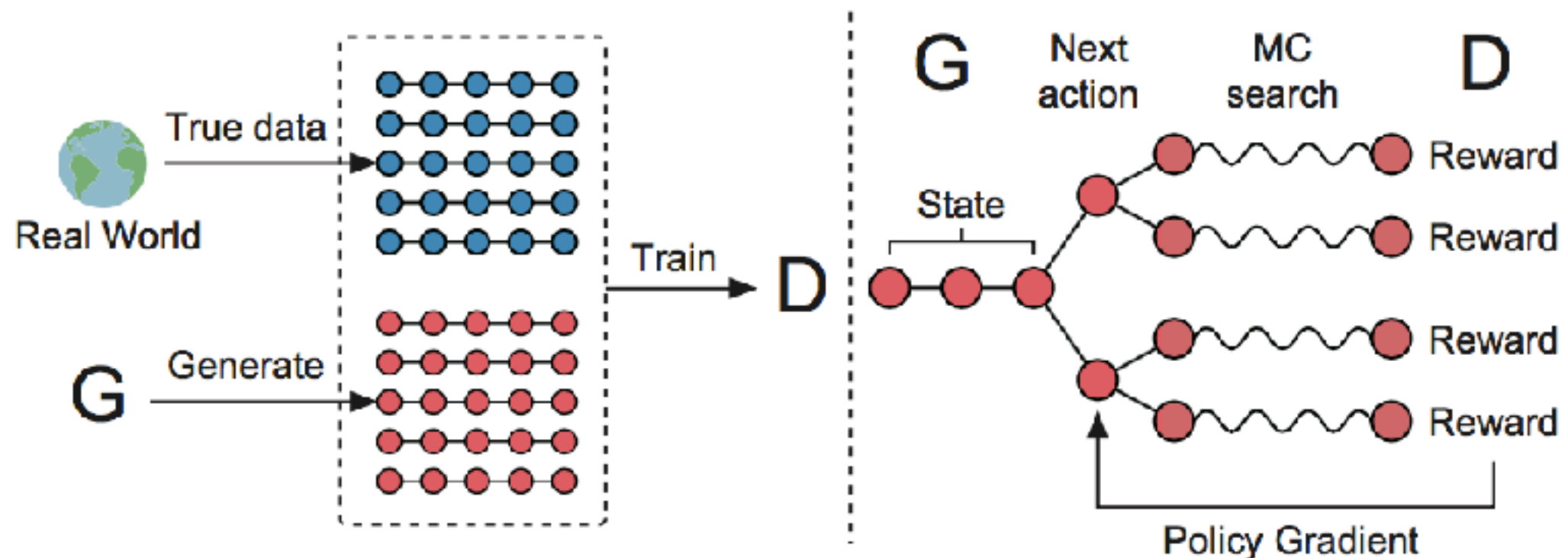
D(this)

D(this is)

D(this is a)

D(this is a fake)

D(this is a fake sentence)

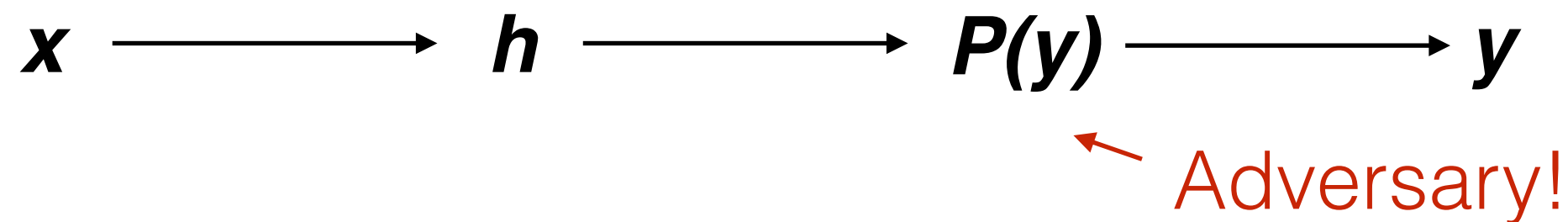# Stabilization Tricks: Performing Multiple Rollouts

- Like other methods using discrete samples, instability is a problem

- This can be helped somewhat by doing multiple rollouts (Yu et al. 2016)

Discrimination over Softmax Results (Hu et al. 2017)

- Attempt to generate outputs with a specific trait (e.g. tense, sentiment)
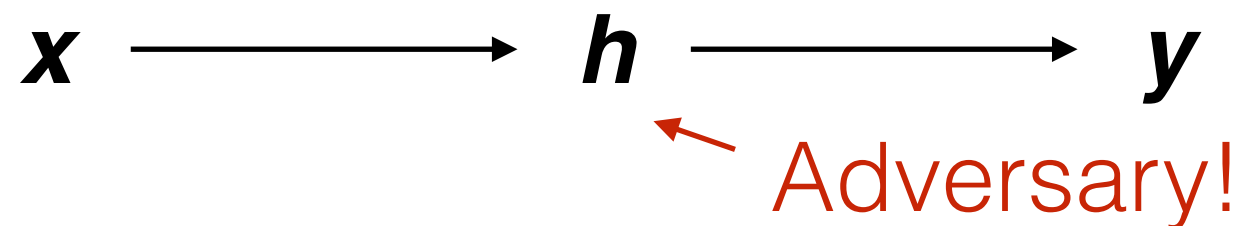
- Discriminator over the softmax results

$$x \longrightarrow h \longrightarrow P(y) \longrightarrow y$$

Adversary!

Adversarial Feature Learning

Adversaries over Features vs. Over Outputs

- Generative adversarial networks

$$x \longrightarrow h \longrightarrow y$$

← Adversary!

- Adversarial feature learning

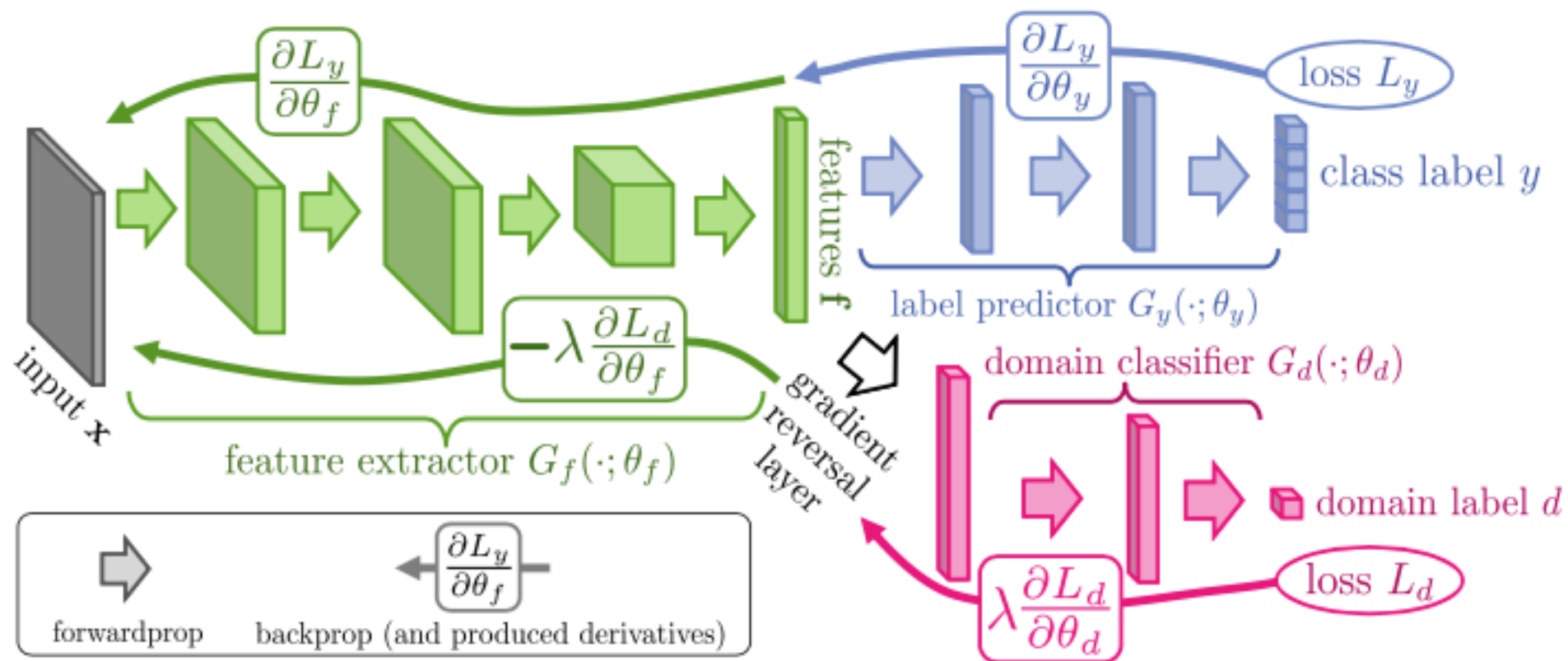$$x \longrightarrow h \longrightarrow y$$

← Adversary!

- Why adversaries over features?
  - Non-generative tasks
  - Continuous features easier than discrete outputs

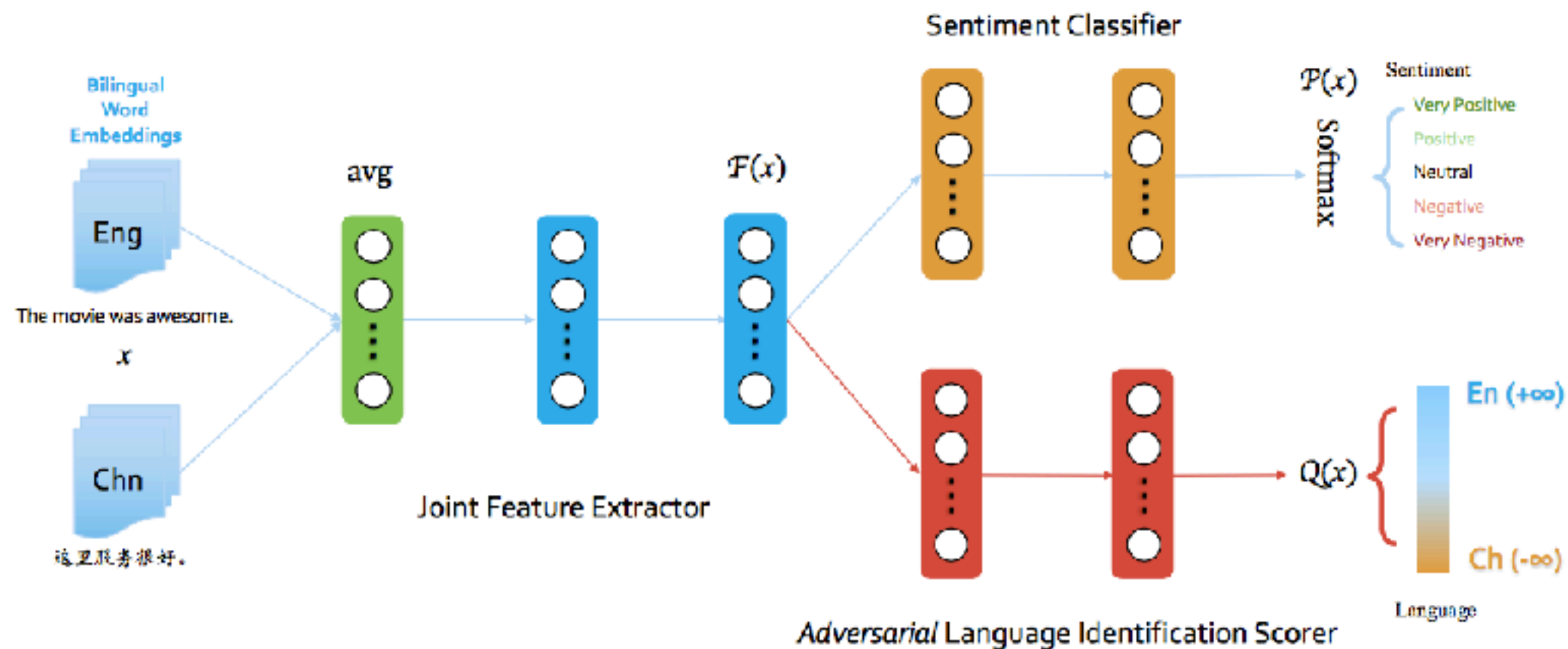# Learning Domain-invariant Representations (Ganin et al. 2016)

- Learn features that cannot be distinguished by domain

- Interesting application to synthetically generated or stale data (Kim et al. 2017)
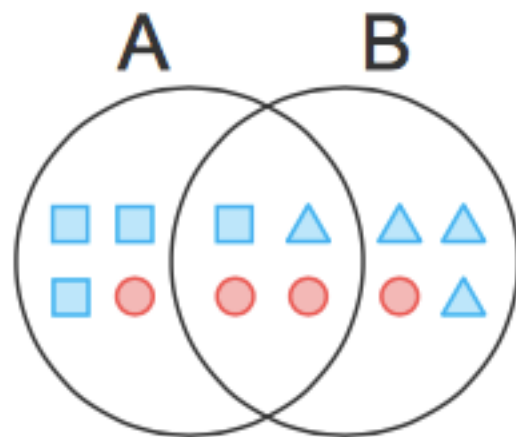
Learning Language-invariant Representations

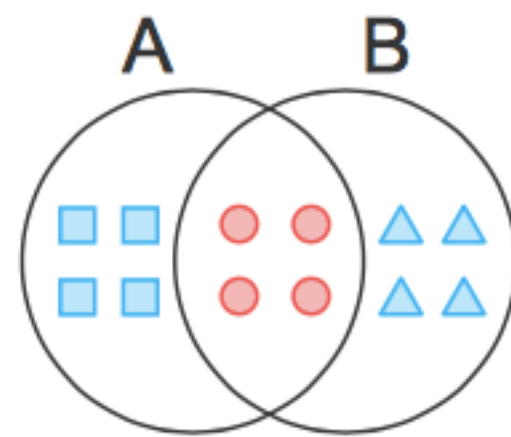- Chen et al. (2016) learn language-invariant representations for text classification

- Also on multi-lingual machine translation (Xie et al. 2017)

Adversarial Multi-task Learning (Liu et al. 2017)

- Basic idea: want some features in a shared space across tasks, others separate


(a) Shared-Private Model   (b) Adversarial Shared-Private Model

- Method: adversarial discriminator on shared features, orthogonality constraints on separate features

Implicit Discourse Connection Classification w/ Adversarial Objective
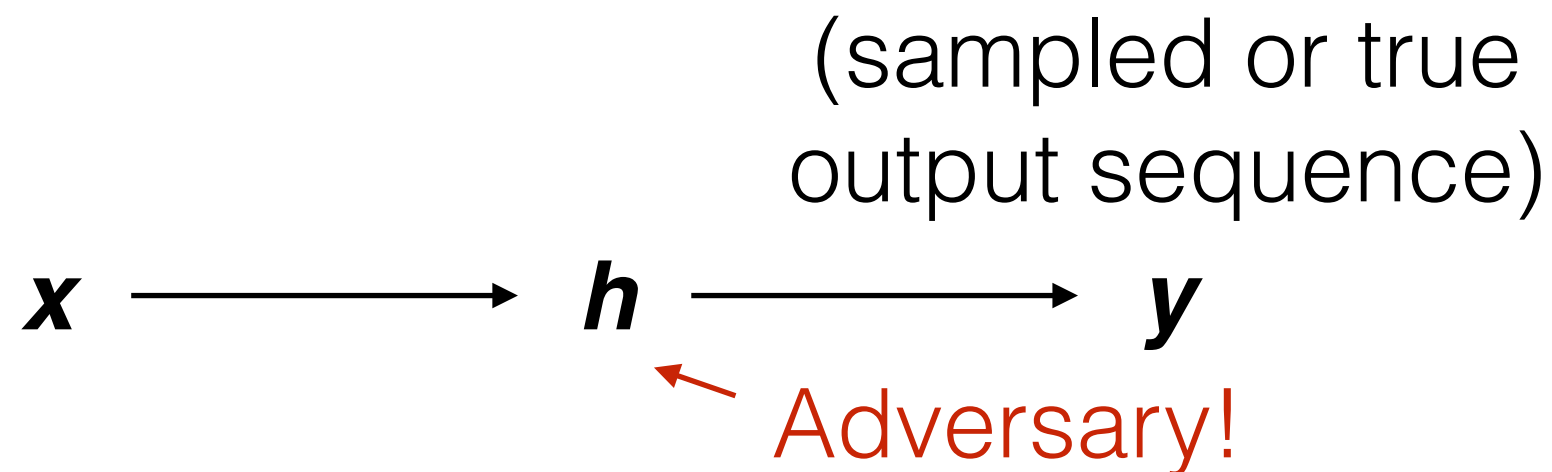
(Qin et al. 2017)

- Idea: implicit discourse relations are not explicitly marked, but would like to detect them if they are

- Text with explicit discourse connectives should be the same as text without!
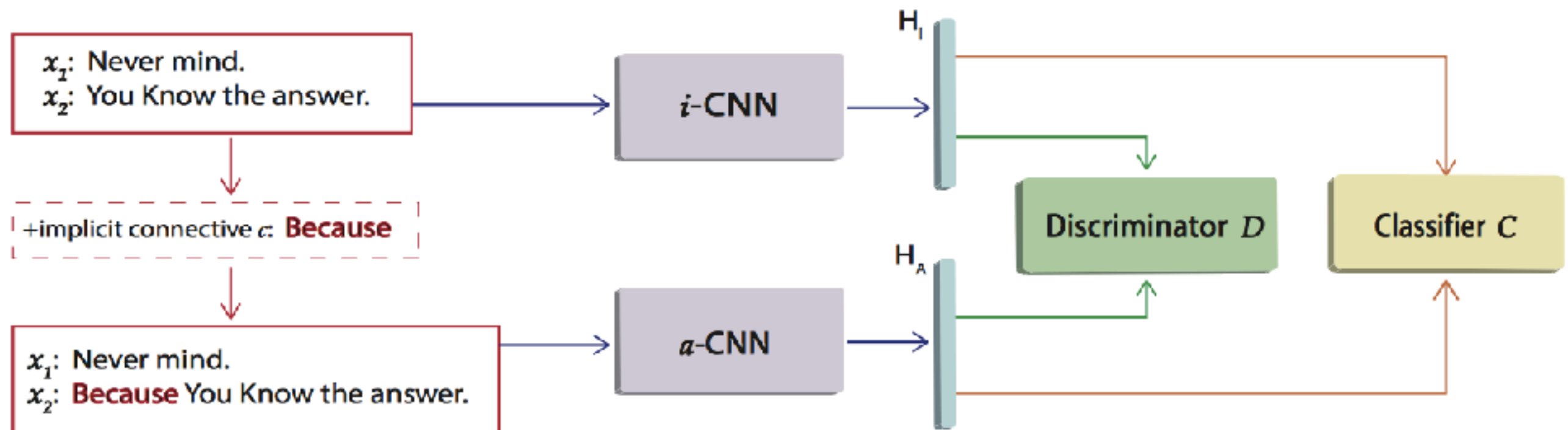
Professor Forcing
(Lamb et al. 2016)

- Halfway in between a discriminator on discrete outputs and feature learning

    - Generate output sequence according to model

    - But train discriminator on hidden states

(sampled or true output sequence)

$x \longrightarrow h \longrightarrow y$
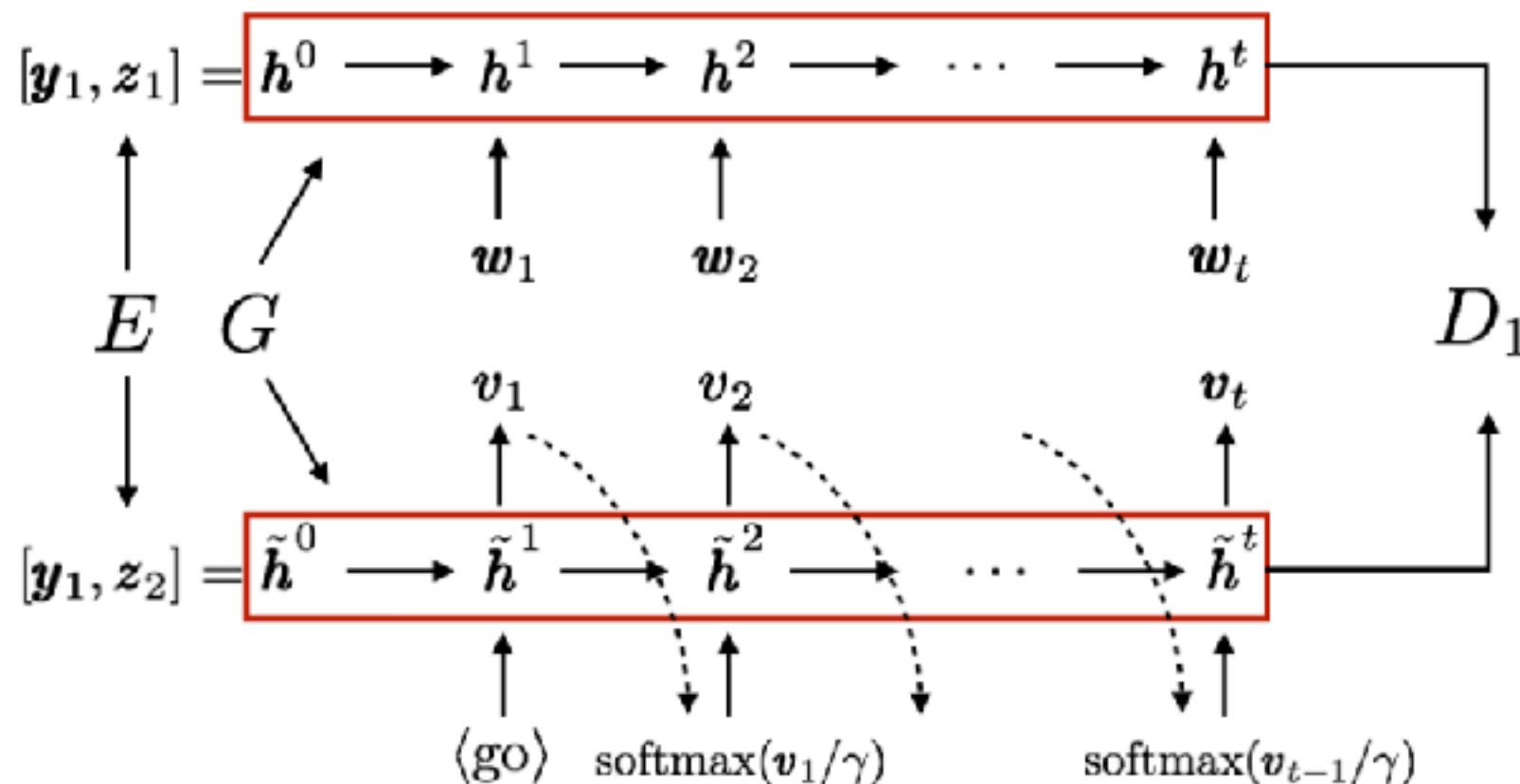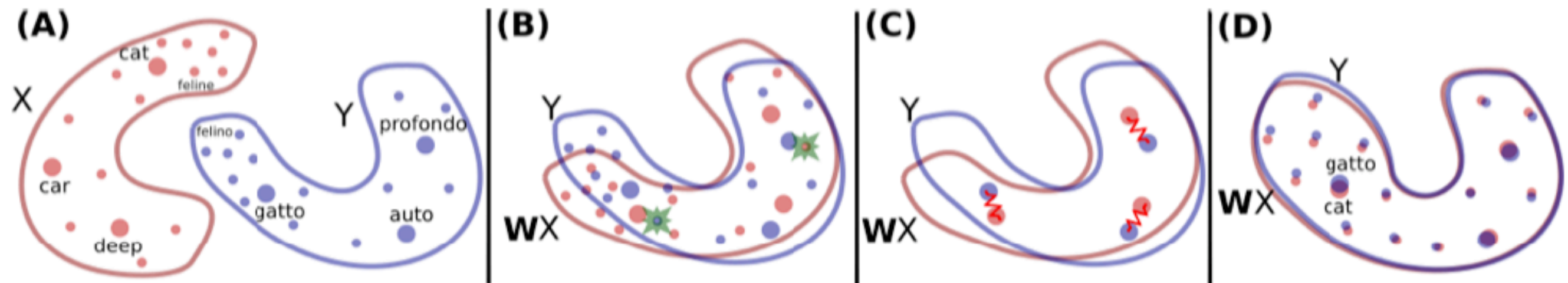
Adversary!

Unsupervised Distribution Matching

Unsupervised Style Transfer for Text (Shen et al. 2017)

- Task: transfer sentences with one style to another style
  - Decipherment: Translate ciphered sentences to natural sentences
  - Transfer sentences with positive sentiment to negative sentiment.
  - Word reordering
- Impressive performance on decipherment

# Unsupervised Alignment of Word Embeddings (Lample et al. 2018)

- We have two word embedding spaces (A) in different languages

- Define a function (e.g. orthogonal transform) to map between the spaces

- Use adversarial loss to try to align (B), further find closest words (C), use supervised objective (D)

Unsupervised Machine Translation
(Lample et al. 2017, Artetxe et al. 2017)

- Cycle consistency (dual learning) (He et al. 2016, Zhu et al. 2017)

- Employing denoising auto-encoder to refine translated sentence
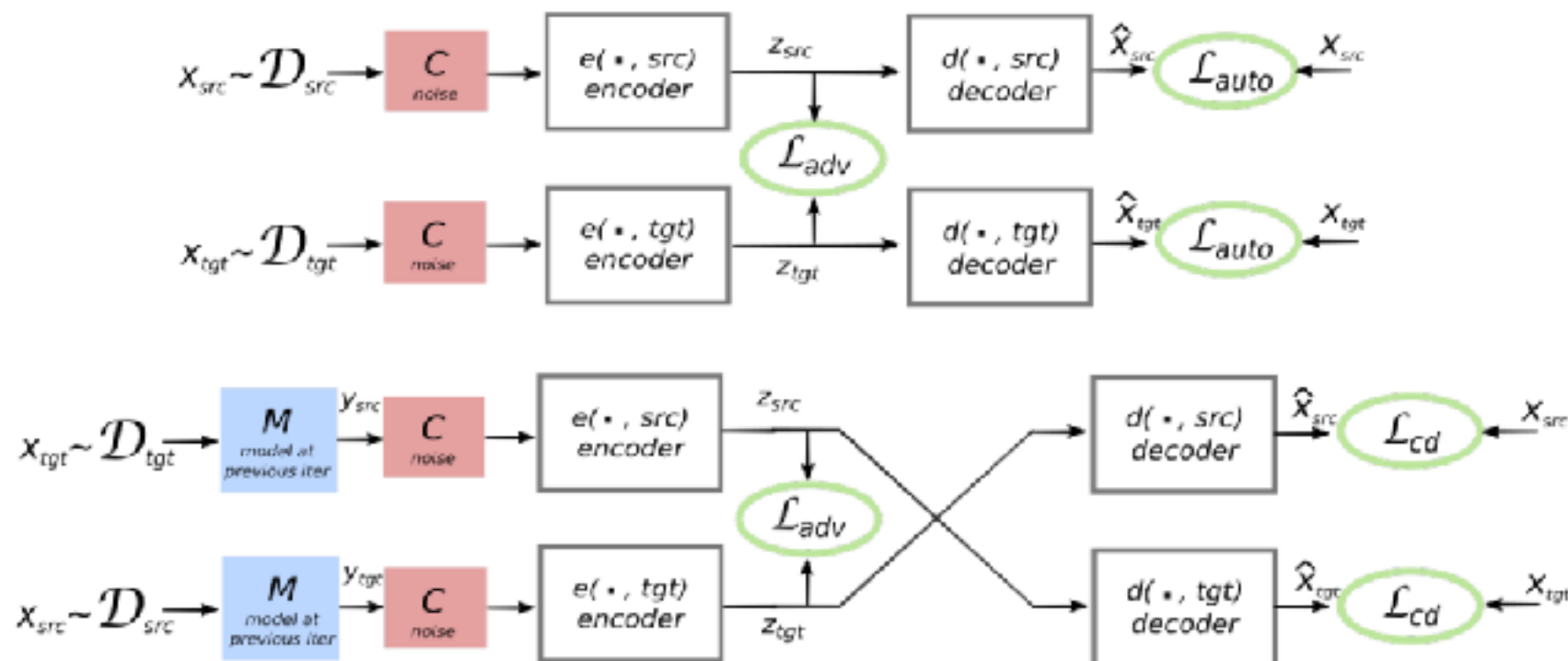
Adversarial Robustness

Problem!
Networks Sensitive to Small Perturbations
(e.g. Belinkov et al. 2018)

Table 4: An example noisy text with human and machine translations.

Input	Luat eienr Stduie der Cambrdige Unievrstit speilt es kenie Rlloe in welcehr Reiehnfogle die Buhcstbaen in eniem Wrot vorkmomen, die eingzie whctige Sahce ist, dsas der ertse und der lettze Buhcstbaen stmimt .
Human	According to a study from Cambridge university, it doesn't matter which order letters in a word are, the only important thing is that the first and the last letter appear in their correct place.
char2char	Cambridge Universttte is one of the most important features of the Cambridge Universttten , which is one of the most important features of the Cambridge Universttten .
Nematus	Luat eienr Stduie der Cambrant Unievrstilt splashed it kenie Rlloe in welcehr Reiehnfogle the Buhcstbaen in eniem Wred vorkmomen, die eingzie whcene Sahce ist, DSAs der ertse und der lettze Buhcstbaen stmimt .
charCNN	According to the <unk> of the Cambridge University , it 's a little bit of crude oil in a little bit of recycling , which is a little bit of a cool cap , which is a little bit of a strong cap , that the fat and the <unk> bites is consistent .
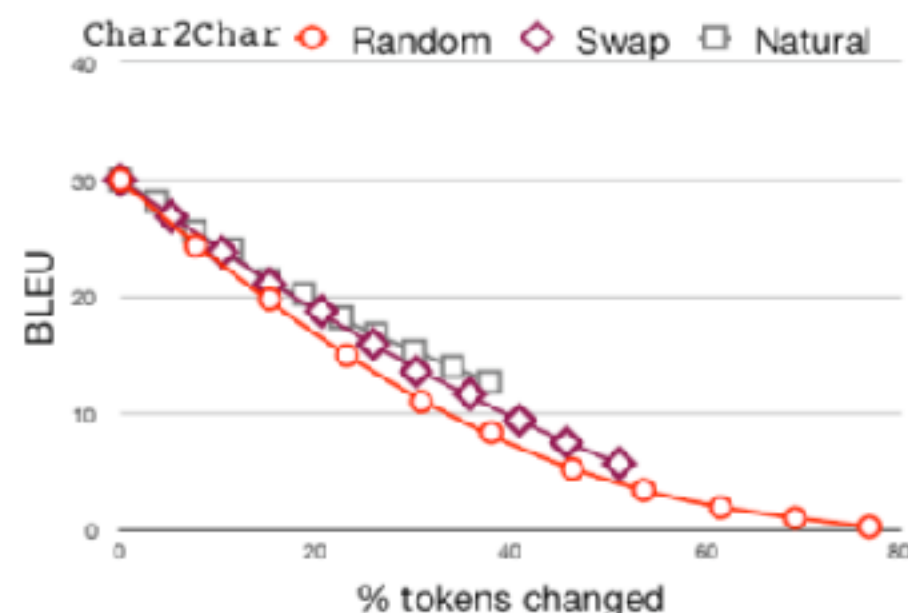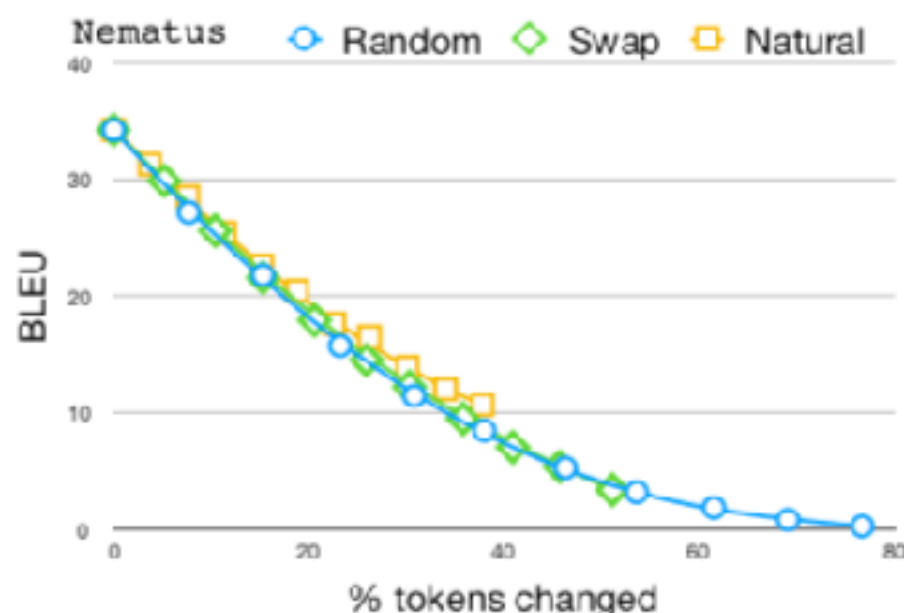
Adversarial Noise:
Noise Specifically Designed to Break Systems

- Relatively simple to perform attacks on image classification systems: calculate gradient to maximize loss

- More difficult for text because input is discrete, but still some success (e.g. Ebrahimi et al. 2018)

src	1901 wurde eine Frau namens Auguste in eine medizinische Anstalt in Frankfurt gebracht.
adv	1901 wurde eine Frau namens **Afuiguste** in eine medizinische Anstalt in Frankfurt gebracht.
src-output	In 1931, a woman named **Augustine** was brought into a medical institution in France.
adv-output	In 1931, a woman named Rutgers was brought into a medical institution in France.
src	Das ist Dr. Bob Childs – er ist Geigenbauer und Psychotherapeut.
adv	Das ist Dr. Bob Childs – er ist Geigenbauer und **Psy6hothearpeiut**.
src-output	This is Dr. Bob Childs – he's a wizard maker and a **therapist**'s **therapist**.
adv-output	This is Dr. Bob Childs – he's a brick maker and a **psychopath**.

Table 1: Controlled and Targeted Attack on DE→EN NMT. In the first example, the adversary wants to suppress a person's name, and in the second example, to replace occurrences of *therapist* with *psychopath*

What is an Adversarial Example? (Michel et al. 2019)

- It should be "meaning preserving" on the source side, and "meaning destroying" on the target side

$$\boxed{1 - s_{src}(x, \hat{x})} < \boxed{d_{tgt}(y, y_M, \hat{y}_M)}$$

Source meaning destruction   **Target meaning destruction**

$$d_{tgt}(y, y_M, \hat{y}_M) = \begin{cases} 0 \text{ if } s_{tgt}(y, \hat{y}_M) \geq s_{tgt}(y, y_M) \\ \frac{s_{tgt}(y, y_M) - s_{tgt}(y, \hat{y}_M)}{s_{tgt}(y, y_M)} \text{ otherwise} \end{cases}$$

- Meaning defined by semantic similarity (whatever that means)

Adversarial Training

- We'd like to train our models to be robust to attacks!

- Simplest idea: sample adversarial examples at training time and make sure that they are also classified correctly

- Lots of theory, but little for NLP tasks

  https://adversarial-ml-tutorial.org

Questions?