Learning to Navigate Unseen Environments: Back Translation with Environmental Dropout

Hao Tan, Licheng Yu, Mohit Bansal
haotan, licheng, mbansal@cs.unc.edu

UNC, Chapel Hill
Go to the bedroom, and go through the door, continue forward until you can climb three steps to your right…
Go to the bedroom, and go through the door, continue forward until you can climb three steps to your right…
Go to the bedroom, and go through the door, continue forward until you can climb three steps to your right…
Go to the bedroom, and go through the door, continue forward until you can climb three steps to your right…
Vision-and-Language Navigation Task

**Instruction**

Go to the bedroom, and go through the door, continue forward until you can climb three steps to your right…
Go to the bedroom, and go through the door, continue forward until you can climb three steps to your right…
Go to the bedroom, and go through the door, continue forward until you can climb three steps to your right…
Go to the bedroom, and go through the door, continue forward until you can climb three steps to your right…
Go to the bedroom, and go through the door, continue forward until you can climb three steps to your right…
Back Translation

1. Want to learn: En → Fr

English → French
Back Translation

1. Want to learn: En → Fr

2. Have unpaired Fr corpus
Back Translation

1. Want to learn: En → Fr
2. Have unpaired Fr corpus
3. Train Fr → En and use it to translate unpaired Fr corpus.

- Improving Neural Machine Translation Models with Monolingual Data, Senrich et al., 2015
- Iterative Back-Translation for Neural Machine Translation, Hoang et al., 2018
- Style Transfer Through Back-Translation, Prabhumoye et al., 2018
- Understanding Back-Translation at Scale, Edunov et al., 2018
Back Translation

1. Want to learn: $\text{En} \rightarrow \text{Fr}$.

2. Have unpaired Fr corpus.

3. Train Fr $\rightarrow$ En and use it to translate unpaired Fr corpus.

4. Use reversed pairs as additional data for $\text{En} \rightarrow \text{Fr}$.

Improving Neural Machine Translation Models with Monolingual Data, Senrich et al., 2015
Iterative Back-Translation for Neural Machine Translation, Hoang et al., 2018
Style Transfer Through Back-Translation, Prabhumoye et al., 2018
Understanding Back-Translation at Scale, Edunov et al., 2018
Back Translation: Preliminary Setup

Environment: A set of routes. Some routes have instructions; Some do not.
Back Translation: Preliminary Setup

Environment: A set of routes. Some routes have instructions; Some do not.

Speaker: A pre-trained neural model which generates instructions from routes.
Back Translation: Step 1

1. **New routes** from **existing environments**.
1. **New routes** from existing environments.
2. **New instructions** by pre-trained speaker.
Back Translation: Step 3

1. **New routes** from existing environments.
2. **New instructions** by pre-trained speaker.
3. **Train agent on** new routes, new instructions, existing environments.
Back Translation: **Limited Envs?**

1. **New routes** from **existing environments**.
2. **New instructions** by **pre-trained speaker**.
3. Train agent on **new routes**, **new instructions**, **existing environments**.

---

**Back Translation**

- **Agent**
  - Walk past the hall, turn Left, ...

**Existing Environment**

**Speaker**

**Agent**
Back Translation: **New Envs!!**

1. New routes from **New environments**.
2. New instructions by pre-trained speaker.
3. Train agent on New routes, New instructions, New environments.
How to get new environments?

Captured from new houses?
How to get new environments?

Captured from new houses?

Is very expensive…

Matterport Pro2
Made for Professionals

- Pro-grade resolution and accuracy
- Powerful battery for scanning multiple properties in a day
- Derivative assets available (floor plans, print-ready photos, and MatterPak™)
- Compatible with the Matterport Professional and Business subscription plans

$3,395 USD
How to get new environments?

Generate new environments?
How to get new environments?

Generate new environments?

Not so easy…
How to get new environments?

Let’s modify the existing environments!!
Illustration: Random Removal

Viewpoints

$O_t,1$

$O_t,2$

Views

$O_{t+1},1$

$O_{t+1},2$

RGB-image views
Illustration: Random Removal

Remove objects (Marked in blue)
Illustration: Random Removal (Two Issues)

Incomplete Removal: The chair is still visible from other views.
Illustration: Random Removal (Two Issues)

Inconsistent Removal:
The same chair disappears in the next viewpoint.

Incomplete Removal:
The chair is still visible from other views.
Illustration: Environmental Removal / Dropout

Solution: Remove all the chairs!!
Environmental Dropout: Image-Level Implementation

Object-level annotation is noisy.

RGB Image

Semantic View
Environmental Dropout: Image-Level

Rendering is slow for training agents.
Environmental Dropout: Feature-Level

Random Feature Dropout

Environmental Dropout
Environmental Dropout: Full Pipeline

Walk past the hall, turn Left, ...

Agent

Speaker

Env Drop

Existing Environment

New Environment
Results Comparison

Metric: Success Rate

Evaluated in Unseen Environments

- Agent
  - Training Environments
  - Testing Environments
Results Comparison

Agent Training

Walk past the hall, turn Left, ...

46.5%
Results Comparison

Agent Training

Agent

Back Translation

Existing Environment

Agent

Speaker

Walk past the hall, turn Left, ...

46.5%

48.2% (+1.7%)
Results Comparison

Agent Training

Back Translation

Back Translation w/ Random Dropout

Agent

Walk past the hall, turn Left, ...

Speaker

Existing Environment

Existing Environment

New Environment

Agent

Walk past the hall, turn Left, ...

Agent

Walk past the hall, turn Left, ...

46.5%

48.2% (+1.7%)

48.4% (+1.9%)
Results Comparison

Agent Training

- Agent: Walk past the hall, turn Left, ...

Back Translation

- Existing Environment

- Speaker: Walk past the hall, turn Left, ...

- Agent

- New Environment

- Env Drop

- Speaker: Walk past the hall, turn Left, ...

- Agent

46.5% 48.2% (+1.7%) 52.2% (+5.7%)
Leaderboard Results

Greedy Decoding

Previous Best: 48.0%

Ours: 51.5% (+3.5%)

Beam Search

Previous Best: 63.0%

Ours: 68.9% (+6.9%)

Self-Monitoring Navigation Agent via Auxiliary Progress Estimation, Ma et al., 2019
If we use “new” environment, the result is better.
Sufficient and Necessary

If we use “new” environment, the result is better.

If we do not use “new” environment, the result would not be better.
Upper Bound of Back Translation (on Existing Envs)

Existing Environments
Upper Bound of Back Translation (on Existing Envs)
Upper Bound of Back Translation (on Existing Envs)

Back Translation

Labeled Data

Unlabeled Data

Labeled Data

Pseudo-labeled Data

Labeled Data

**Labeled** Data

“Weaker Than” Assumption
Upper Bound of Back Translation (on Existing Envs)

Back Translation

Existing Environments

Labeled Data

Unlabeled Data

Pseudo-labeled Data

**Labeled** Data
Upper Bound of Back Translation (on Existing Envs)

How to calculate (approximate) this upper bound?
Upper Bound of Back Translation (on Existing Envs)

How to calculate (approximate) this upper bound?

“Result Extrapolation” Approximation
“Result Extrapolation” Approximation

26% Training data

73% Training data

100% Training data

Labeled Data

**Labeled** Data

Predict

**52%**
Reinforcement Learning + Imitation Learning

RL:
Agent <BOS>
Agent <BOS>
Agent <BOS>

IL:
Agent <BOS>
Agent <BOS>
Teacher Actions

Sampling
Sampling
Rewards

Walk past the shelves and out of the garage. Stop in ...
Thank you!

Hao Tan, Licheng Yu, Mohit Bansal

Code released at:
https://github.com/airsplay/R2R-EnvDrop

UNC Chapel Hill

Supported by ARO-YIP, ONR, Google, Facebook, Adobe, Baidu, and Salesforce.