Neural Inverse Knitting:
From Images to Manufacturing Instruction

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Pacific Ballroom #137, http://deepknitting.csail.mit.edu
Industrial Knitting

• Whole garments from scratch

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Industrial Knitting

• Control of individual needles
• Whole garments from scratch

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Knitted Garment & Patterns

Many garments are knitted:

- Beanies, scarves
- Gloves, socks and underwear
- Sweaters, sweatpants

Current machines can create those garments **seamlessly** (no sewing needed).
Knitted Garment & Patterns

Those garments have various types of surface patterns (knitting patterns).

These can be fully controlled by industrial knitting machine.

= User customization!
Machine Knitting Programming

Low-level machine code requires skilled experts = knitting masters

Good news

• Many hand knitting patterns available online and in books
• Online communities of knitting enthusiasts sharing patterns
Scenario

1. User takes picture of knitting pattern
Scenario

1. User takes picture of knitting pattern
2. System creates knitting instructions
Scenario

1. User takes picture of knitting pattern
2. System creates knitting instructions
3. User reuses pattern for new garment

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Dataset: DSL

Domain Specific Language (DSL) for regular knitting patterns

Basic operations

Cross operations

Move operations

Stack Order

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Dataset: Capture

Capture setup with steel rods to normalize tension

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Dataset Content

• Paired instructions with real (2,088) and synthetic (14,440) images.
• Available on project page.

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Learning Problem

Mapping **images** to discrete instruction maps = CE loss minimization

Using two domains of input data (one real, one synthetic) = How to best combine both
Generalization Bound with Two Domains

With probability at least $1 - \delta$

$$\frac{1}{2} |\mathcal{L}_T(\hat{h}, y) - \mathcal{L}_T(h^*_T, y)|$$

Generalization gap

$$\leq \alpha (\text{disc}_\mathcal{H}(\mathcal{D}_S, \mathcal{D}_T) + \lambda) + \epsilon$$

Ideal min.
Generalization Bound with Two Domains

With probability at least $1 - \delta$

$$\frac{1}{2} \left| \mathcal{L}_T(\hat{h}, y) - \mathcal{L}_T(h^*_T, y) \right| \leq \alpha \left( \text{disc}_\mathcal{H}(\mathcal{D}_S, \mathcal{D}_T) + \lambda \right) + \epsilon$$

Generalization gap

Ideal min.

Empirical min. \hspace{1cm} \arg \min_h \alpha \mathcal{L}_S(h, y) + (1 - \alpha) \mathcal{L}_T(h, y)
Generalization Bound with Two Domains

With probability at least $1 - \delta$

$$\frac{1}{2} | \mathcal{L}_T(\hat{h}, y) - \mathcal{L}_T(h^*_T, y) | \leq \alpha \left( \text{disc}_H(\mathcal{D}_S, \mathcal{D}_T) + \lambda \right) + \epsilon$$
Generalization Bound with Two Domains

With probability at least $1 - \delta$

$$\frac{1}{2} |\mathcal{L}_T(\hat{h}, y) - \mathcal{L}_T(h^*_T, y)| \leq \alpha \left( \text{disc}_H(\mathcal{D}_S, \mathcal{D}_T) + \lambda \right) + \epsilon$$

$$\epsilon(m, \alpha, \beta, \delta) = \sqrt{\frac{1}{2m} \left( \frac{\alpha^2}{\beta} + \frac{(1-\alpha)^2}{1-\beta} \right) \log\left(\frac{2}{\delta}\right)}.$$
Generalization Bound with Two Domains

With probability at least $1 - \delta$

$$\frac{1}{2} | \mathcal{L}_T(\hat{h}, y) - \mathcal{L}_T(h^*_T, y) | \leq \alpha \left( \text{disc}_\mathcal{H}(\mathcal{D}_S, \mathcal{D}_T) + \lambda \right) + \epsilon$$

$$\lambda = \min_{h \in \mathcal{H}} \mathcal{L}_S(h, y) + \mathcal{L}_T(h, y).$$

Ideal error of the combined losses
Generalization Bound with Two Domains

With probability at least $1 - \delta$

$$\frac{1}{2} | \mathcal{L}_T(\hat{h}, y) - \mathcal{L}_T(h^*_T, y)| \leq \alpha \left( \text{disc}_H(\mathcal{D}_S, \mathcal{D}_T) + \lambda \right) + \epsilon$$

Discrepancy between distributions

$$\text{disc}_H(\mathcal{D}_S, \mathcal{D}_T) = \max_{h, h' \in \mathcal{H}} | \mathcal{L}_{\mathcal{D}_S}(h, h') - \mathcal{L}_{\mathcal{D}_T}(h, h') |$$
Data distributions

• Two different distribution types

$D_S$  
Real data

$D_T$  
Synthetic data
Data distributions

- Two different distribution types

\[ D_S \quad \text{Real data} \]

\[ D_T \quad \text{Synthetic data} \]
From synthetic to real

- S+U Learning [Shrivastava’17]

\[
\min_{M} \text{disc}(D_S, M(D_T))_{S \leftrightarrow T}
\]
From synthetic to real

• S+U Learning [Shrivastava’17]

\[
\min_{M} \text{disc}(\mathcal{D}_S, M(\mathcal{D}_T)) \\
\]

Real-looking data

Synthetic data

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From synthetic to real

• One-to-many mapping!

$M(\cdot)$

$\min_M \text{disc}(\mathcal{D}_S, M(\mathcal{D}_T))_{S \leftrightarrow T}$

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From synthetic to real

• One-to-many! 😞

\[
\min_M \text{disc}(\mathcal{D}_S, M(\mathcal{D}_T))_{S \leftrightarrow T}
\]

Tension  Lighting  Color  Yarn

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From real to synthetic

• Many-to-one!

\[
\min_M \text{ disc}(M(D_S), D_T)_{S \rightarrow T}
\]
Network composition