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# Machine Learning and Deep Learning Conference 2019

SAND2019-9054C

## SAR ATR Using Deep Latent Spaces

July 29, 2019

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Funded by LDRD

## Problem Overview

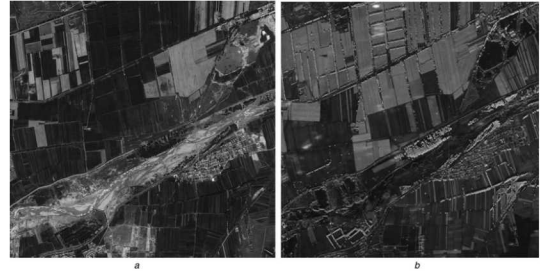
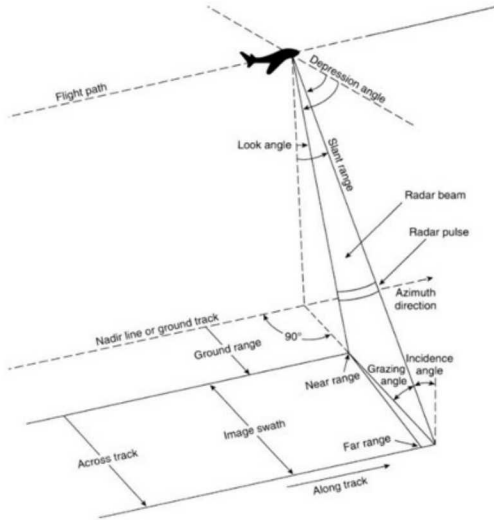
State-of-the-Art

Siamese Variational Autoencoder

Results

Future Work

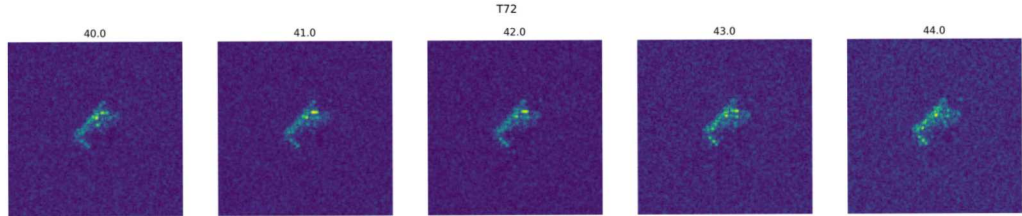
# SAR images are significantly different than optical images.



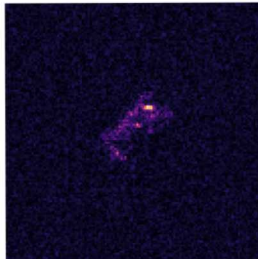
a. Optical b. SAR

Image from [https://www.researchgate.net/figure/Comparison-of-the-optical-images-of-Earth-surface-and-the-SAR-image-a-Optical-satellite\\_fig2\\_301598943](https://www.researchgate.net/figure/Comparison-of-the-optical-images-of-Earth-surface-and-the-SAR-image-a-Optical-satellite_fig2_301598943)

# SAR Automatic Target Recognition (ATR) is difficult.



Standard Deviation



Problem Overview

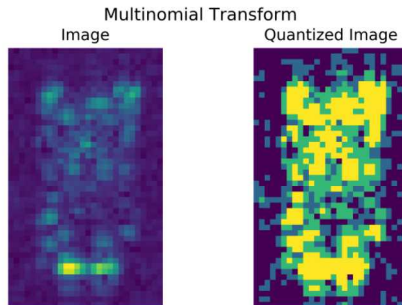
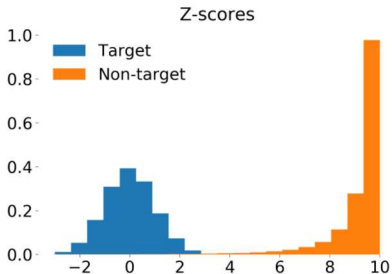
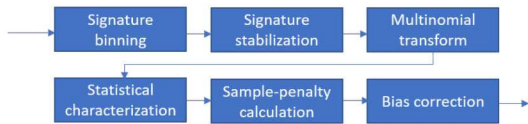
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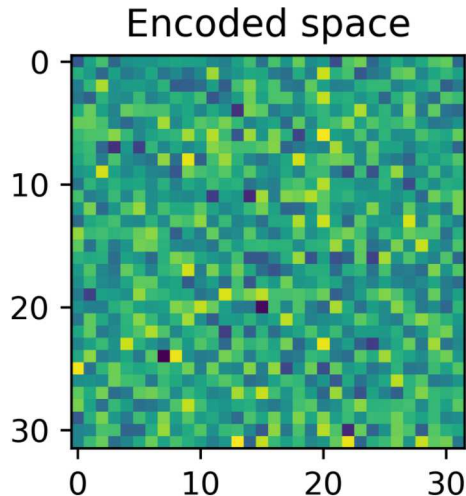
# The state-of-the-art SAR ATR algorithm is Multinomial Pattern Matching (MPM).



$$Z = \frac{1}{C} \sum_{k=1}^K t_{k,q_k}$$

# We would like to improve upon MPM using deep learning.

- Can we bin at larger geometry bins?
- Can we become shift invariant?
- Can we remove the need for a mask?
- Can we enable low-shot learning by synthesizing data?



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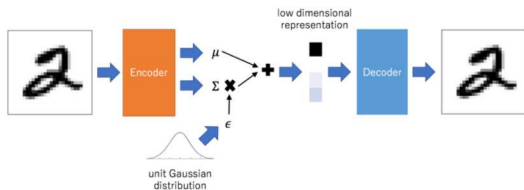
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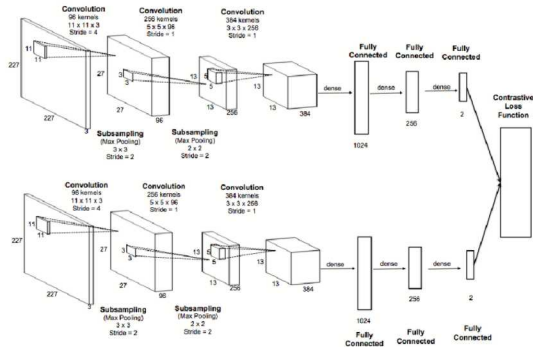


# Some background on applicable deep architectures.

## Variational Autoencoder



## Siamese Network



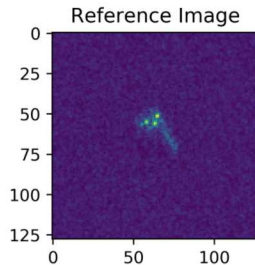
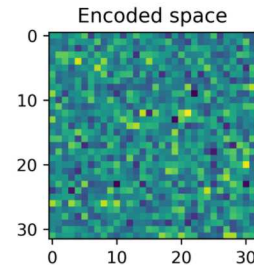
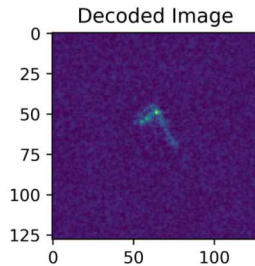
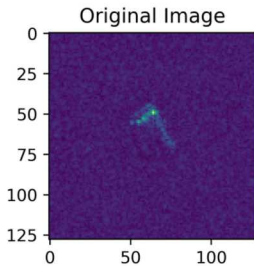
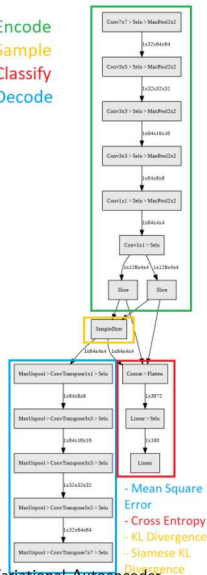
<https://www.semanticscholar.org/paper/>

A-Deep-Siamese-Neural-Network-Learns-the-Similarity-Rao-Wang/

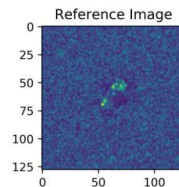
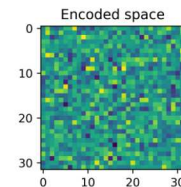
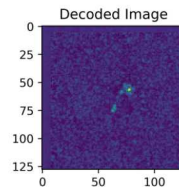
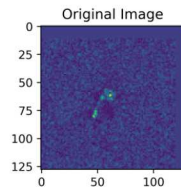
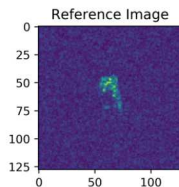
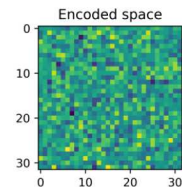
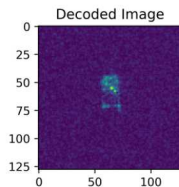
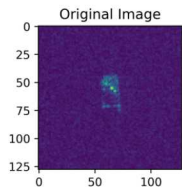
3e16932979250e66cd2cb4d8c9a5411e195273be

# We propose a Siamese Variational Autoencoder (SVAE).

Encode  
Sample  
Classify  
Decode



# Example outputs from SVAE.



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# We have run several experiments for MPM.



## SVAE Training Information

- Trained using synthetic data spanning 25-35 degrees depression angle
- Trained using binning of 20 degrees aspect angle for reference

## TMPM Training Information

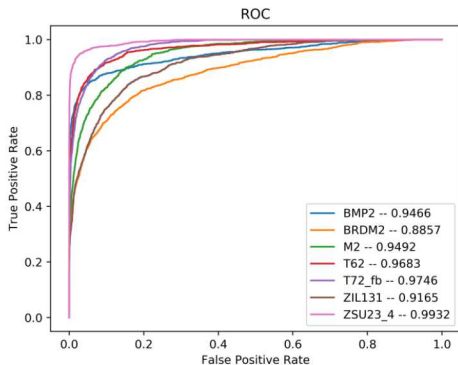
- Trained on 25-30 degrees depression angle
- Tested on 31-35 degrees depression angle

## Experiments

- Train TMPM directly on data, bin in 5 degrees and 20 degrees, with masks
- Train TMPM directly on data, bin in 5 degrees and 20 degrees, without masks
- Train TMPM on embedding, bin in 5 degrees and 20 degrees
- Train TMPM on embedding, bin in 5 degrees and 20 degrees, with shifts in data

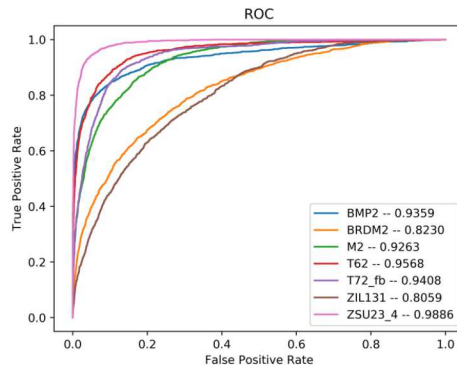
# Baseline MPM – with masks

5 degrees



84.5% Accurate

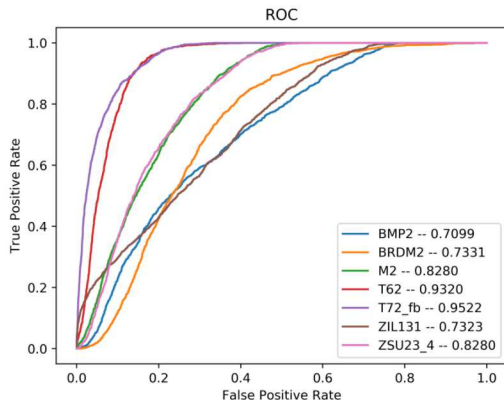
20 degrees



73.5% Accurate

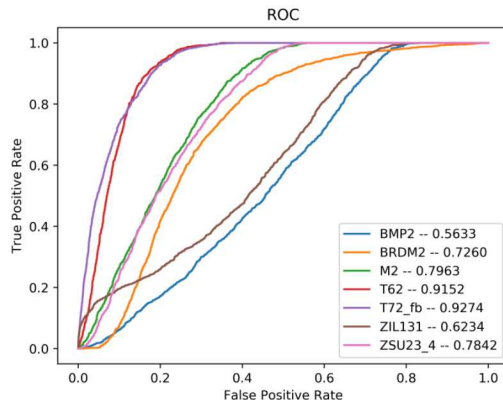
# Baseline MPM – no masks

5 degrees



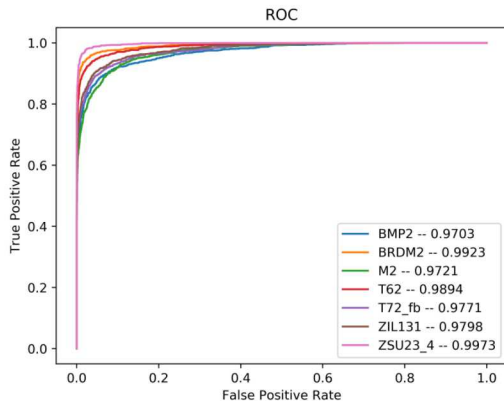
76.4% Accurate

20 degrees



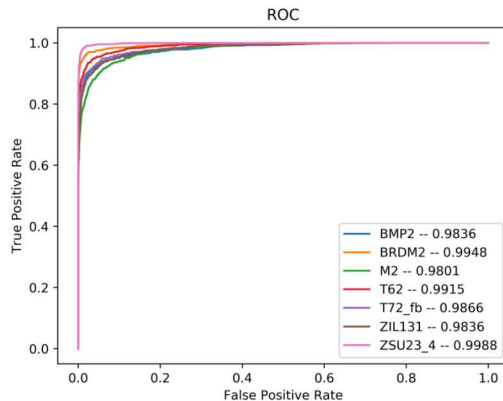
55.6% Accurate

5 degrees



99.9% Accurate

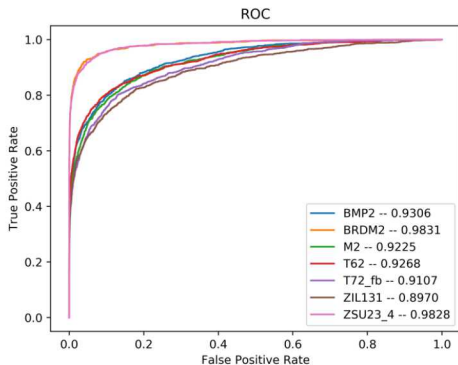
20 degrees



99.97% Accurate

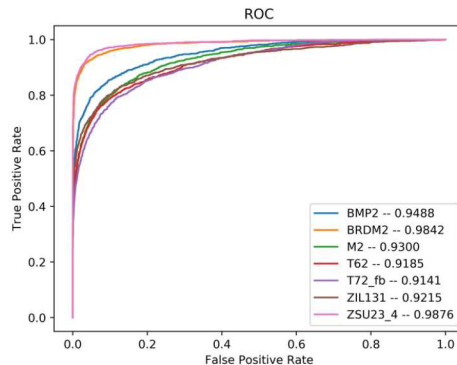


## 5 degrees



97.6% Accurate

## 20 degrees



98.6% Accurate

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- Train SVAE on reduced number of targets to reduce data overlap
- Low-shot learning using SVAE from synthetic data
- Hyperparameter tuning of TMPM in this new space
- Analyze trade-offs between bin geometry and performance
- Train on synthetic, test on real
- Evaluate on data from multiple sensor models