PerceptNet: Learning perceptual similarity of haptic textures in presence of unorderable triplets

Priyadarshini[1] , Siddhartha Chaudhuri[1,2], and Subhasis Chaudhuri[1]

[1]IIT Bombay, [2]Adobe Research

IEEE WHC 2019

July 10, 2019

Goal – To model perceptual dissimilarity between haptics textures

Important aspects

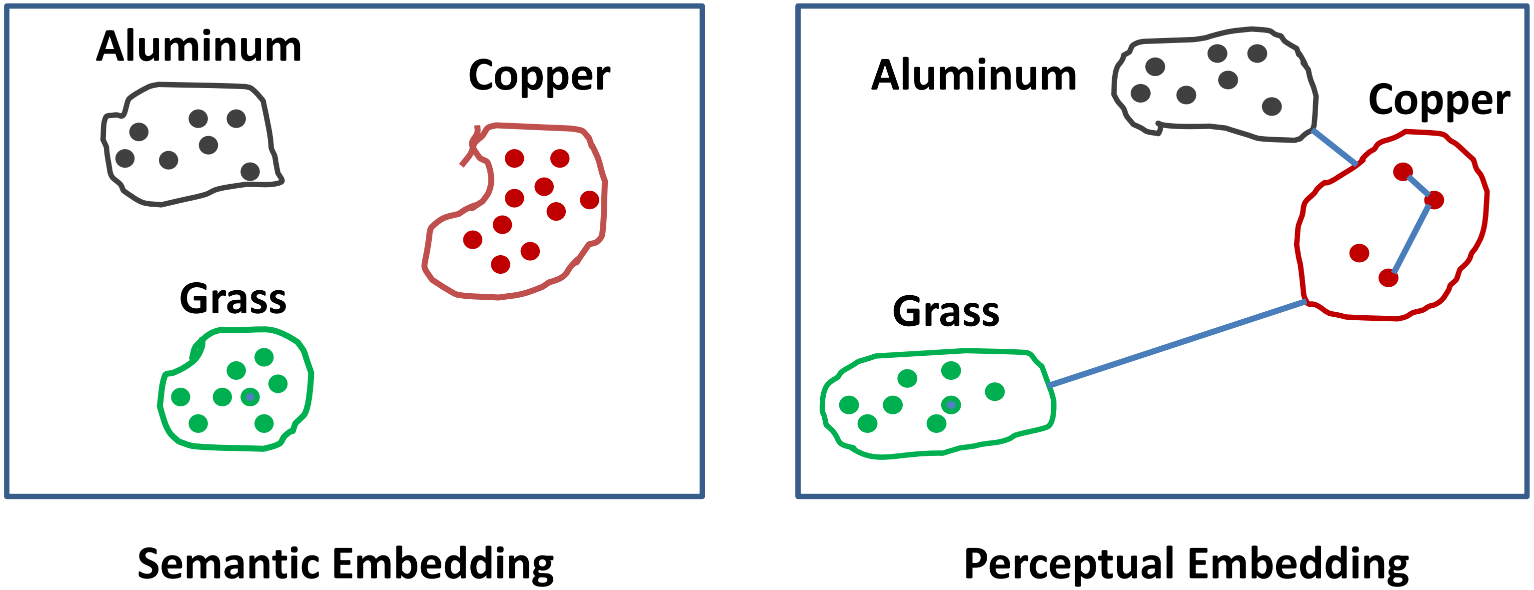
- Incorporate human notion of perceptual dissimilarity

- Model wide range of perceptual dissimilarity (highly similar to highly dissimilar)

- Embed new signals without retraining the model from scratch

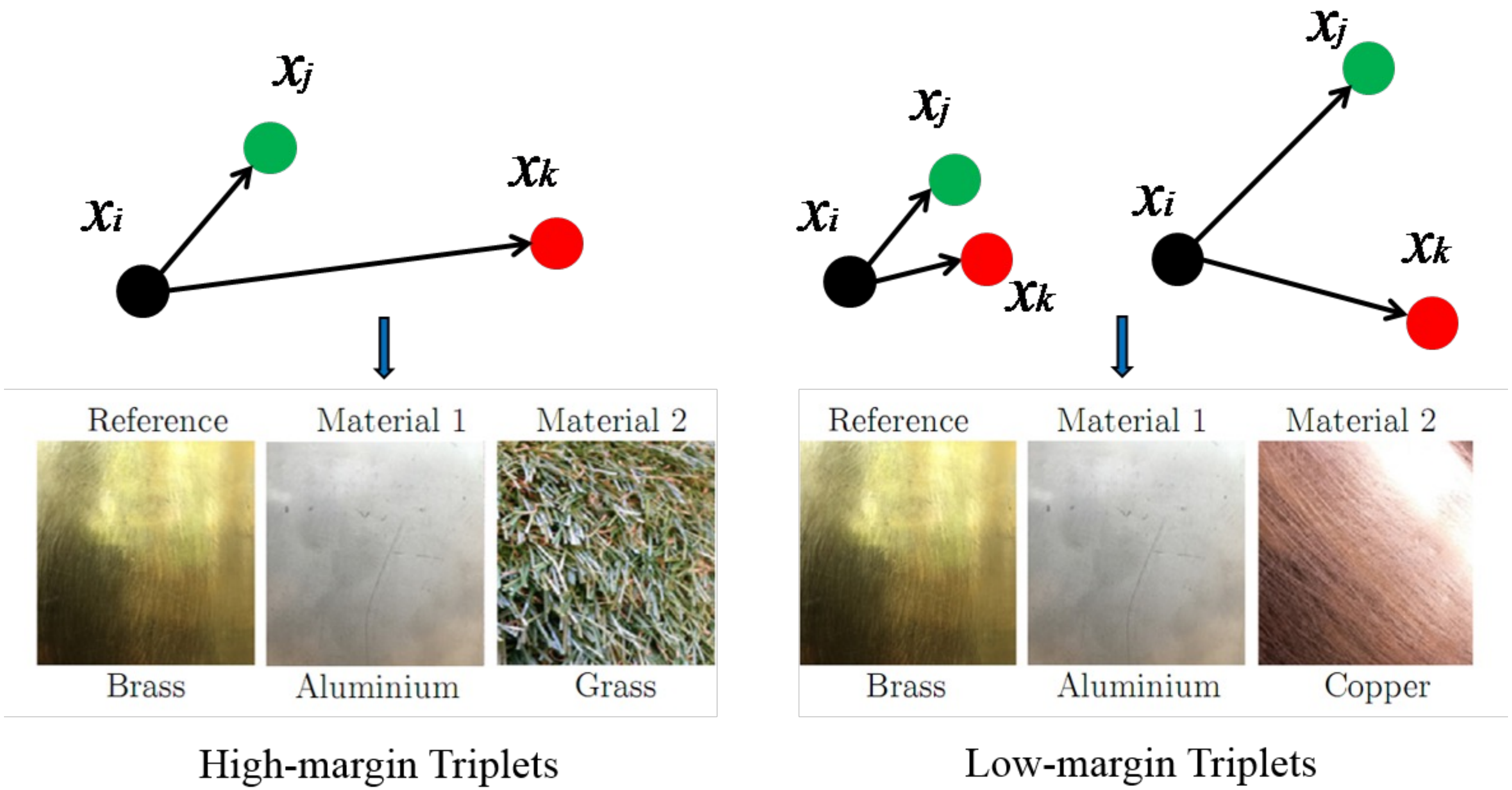
https://phys.org/

Key Idea 1



Objective is to preserve human perceived relative dissimilarity between clusters

Key Idea 2



Low-margin triplets are informative in modeling perceptual dissimilarity in entirety

Key Idea 3

Perceptual Embedding Methods

Parametric

- Allows out-of-sample extension [1, 2,3]
- Can incorporate low-margin triplets
- Can be formulated in terms of relative as well as quantitative similarity [1, 2, 3]

Non-Parametric

- Does not work on new sample [4, 5, 6]
- Does not incorporate low-margin triplets [4, 5, 6]
- Typically formulated in terms of quantitative dissimilarity [4, 5]

1-Richard et al. CVPR2018, 2- Brian et al. JMLR2011, 3- Rui et al. ICASSP 2017, 4-Enriqz et al.ICMI 2006, 5-Sameer et al. AISTATS 2007, 6-Lauren et al. IWMLSP 2012

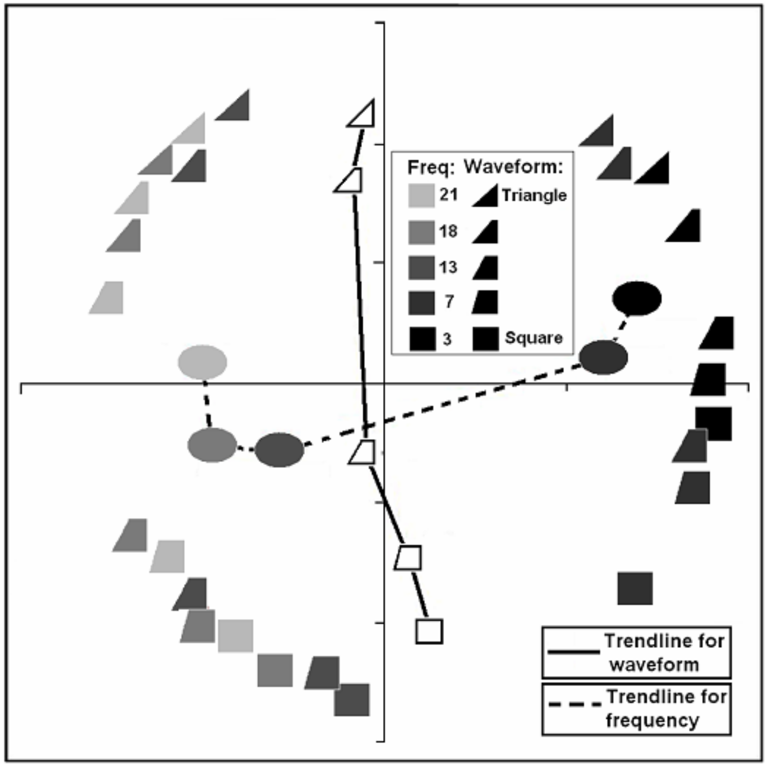
Perceptual Embedding of Haptic Texture

Related work

Goal: To design a set of well distinguishable haptic icons

Input data: 25 haptic stimuli

Method: MDS is used to select 9 most separable stimuli

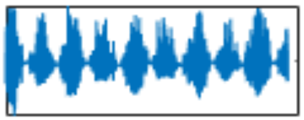


Limitations:

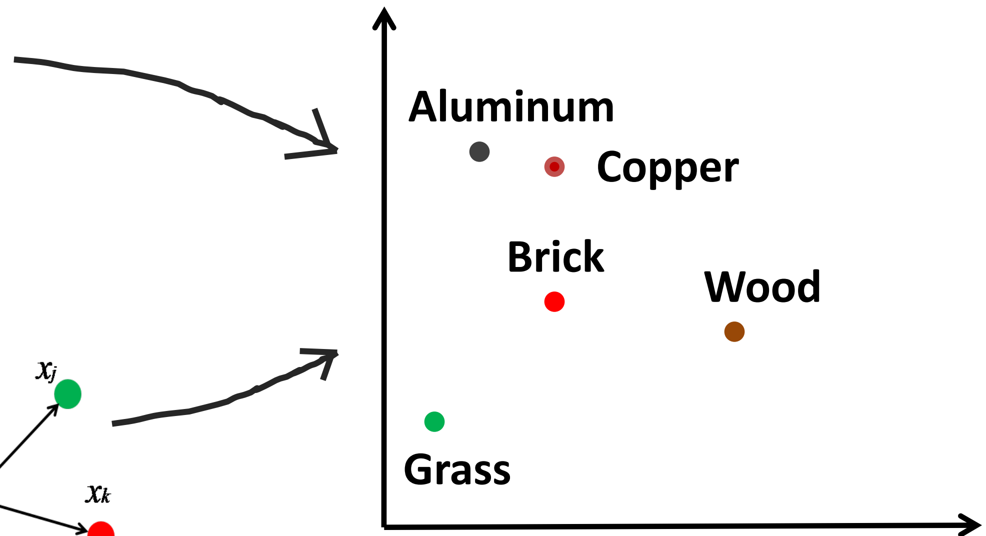
- Requires users dissimilarity rating for all possible signal pairs
- Requires numerical estimates of pair-wise distance
- Non-parametric approach
- Fails to incorporate uncertainty in comparisons

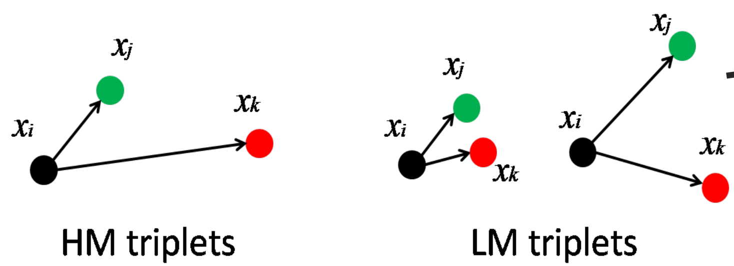
Enriqz et. At ICMI - 2006

Our Method



$$X = \{x_i\}_1^m \in R^n$$





Advantages

- Generalizes to unseen signals
- Works even with partial training data
- Requires non-numerical relative comparisons of signals
- Accommodates both types of triplets

Our Method

To learn an embedding function $\phi : R^n \rightarrow R^m$ such that the Euclidean distance $d_\phi(x, y) = \| \phi(x) - \phi(y) \|$ satisfies:

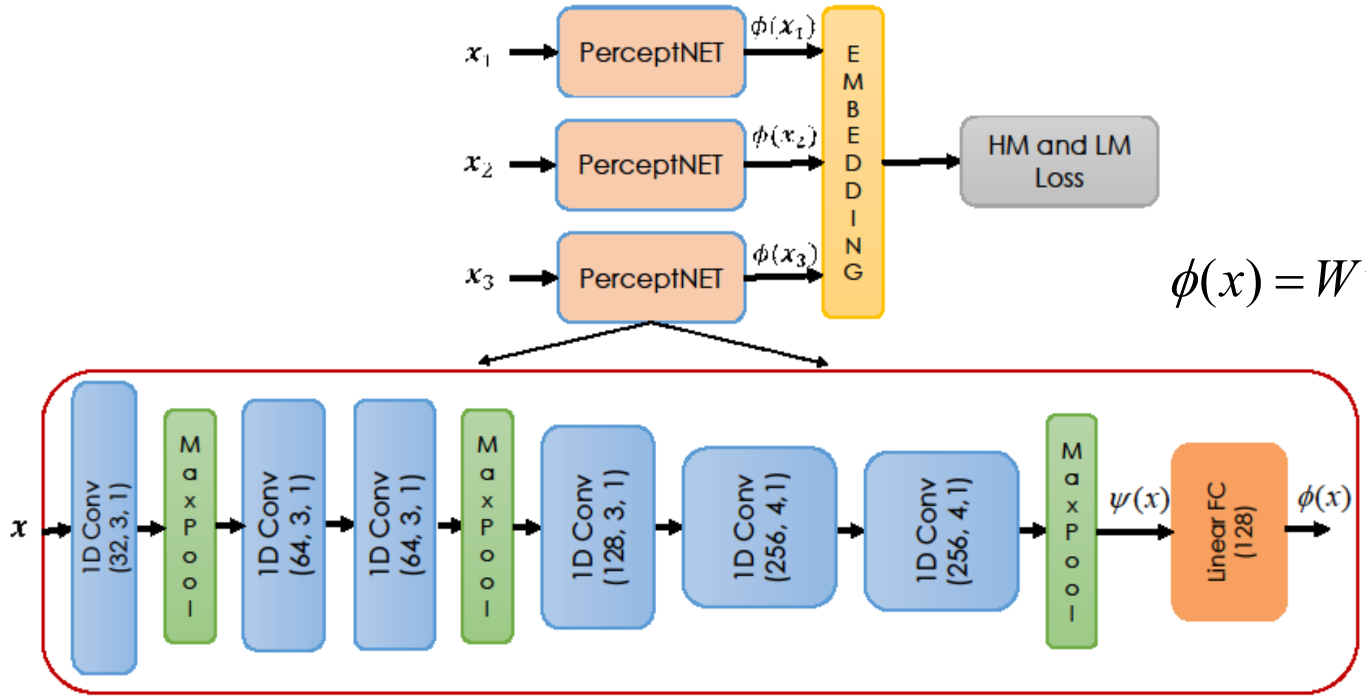
$$d_\phi(x_i, x_k) - d_\phi(x_i, x_j) \geq \xi_\phi \text{ if } (x_i, x_j, x_k) \in H$$

$$| d_\phi(x_i, x_k) - d_\phi(x_i, x_j) | < \xi_\phi \text{ if } (x_i, x_j, x_k) \in L$$

We use a deep neural network(DNN) to learn ϕ

ξ_ϕ : Hyper-parameter

Our Method



$$\phi(x) = W^T \psi(x)$$

$$d_\phi(x, y) = \| \phi(x) - \phi(y) \| = \| W^T (\psi(x) - \psi(y)) \|$$

$$\sqrt{(\psi(x) - \psi(y))^T W W^T (\psi(x) - \psi(y))}$$

$$\sqrt{(\psi(x) - \psi(y))^T M (\psi(x) - \psi(y))}$$

Our Method

Based on the type of triplet, distance margin is penalized by following loss function

$$\min_{\phi} \sum_{c \in H} \exp(-\rho(c)) + \sum_{c \in L} 1 - \exp(-|\rho(c)|)$$

$$\rho((x_i, x_j, x_k)) = d_{\phi}^2(x_i, x_k) - d_{\phi}^2(x_i, x_k)$$

Network is trained iteratively using standard backpropagation technique

Experiments

Input – CQFB features of acceleration signals recorded from 108 classes (metal, grass, etc) with 10 samples each and GT perceptual distance $d^*(x, y)$ of each pair of classes

Ground-truth

$d^*(x, y)$ - Fraction of subjects (out of 30) could distinguish between corresponding classes

ξ^* - 10% of the maximum margin over all possible triplets of signal

Triplets generation

$$H = \{(x_i, x_j, x_k) \mid d^*(x_i, x_k) - d^*(x_i, x_j) \geq \xi^*\}$$

$$L = \{(x_i, x_j, x_k) \mid |d^*(x_i, x_k) - d^*(x_i, x_j)| < \xi^*\}$$

Stresse et al. TOH 2017

Experiments

Evaluation

Triplet generalization accuracy (TGA) - Fraction of satisfied triplet constraints in a test set

$$d_\phi(x_i, x_k) - d_\phi(x_i, x_j) \geq \xi_\phi \ \text{ if } (x_i, x_j, x_k) \in H_{test}$$

$$| d_\phi(x_i, x_k) - d_\phi(x_i, x_j) | < \xi_\phi \ \text{ if } (x_i, x_j, x_k) \in L_{test}$$

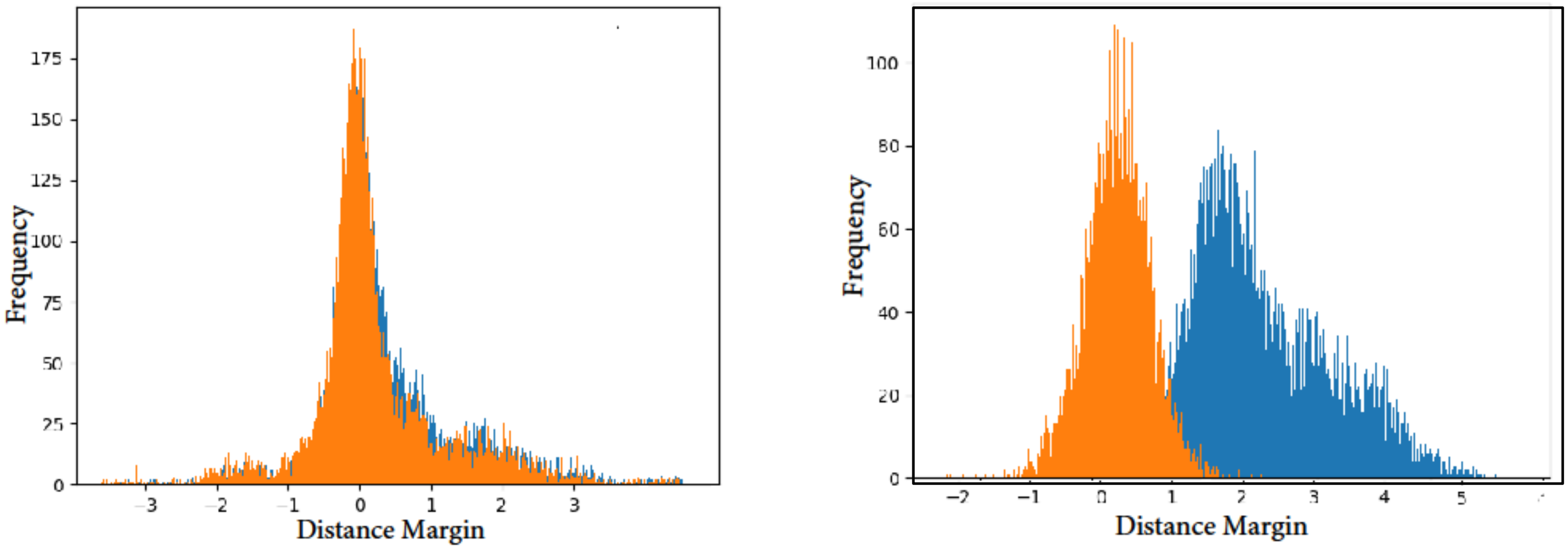
ξ_ϕ is estimated by minimizing $| f_H - f_L |$ where

f_H - fraction of high-margin correctly classified training triplets

f_L - fraction of low-margin correctly classified training triplets

Experimental Results

Histogram of test triplet margins



Distribution of learned high-margin (blue) and low-margin (orange) triplet in Mahalanobis space (left) and in PerceptNet space (right)

Experimental Results

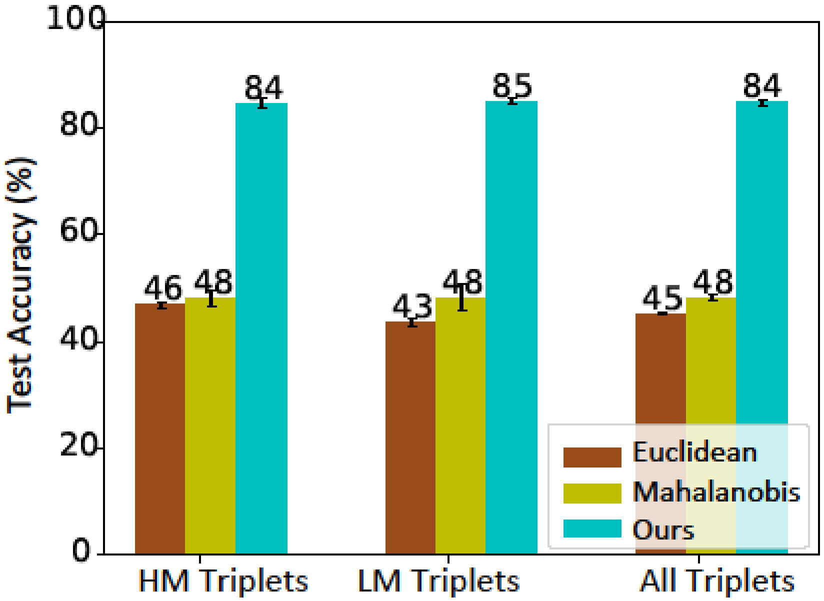
Three variants of experimental protocol-

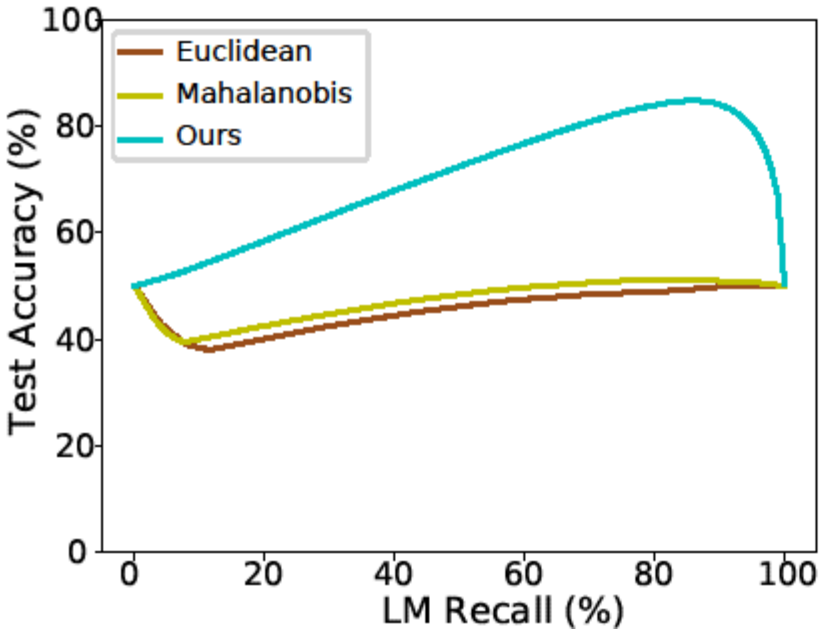
- **Held-Out Triplets** – 50% of triplets are held-out for testing , however the samples and classes are common for training and testing

- **Held-Out Samples-** 20% samples from each class are held-out for testing

- **Held-Out Classes-** All samples from 20% class are held-out for testing

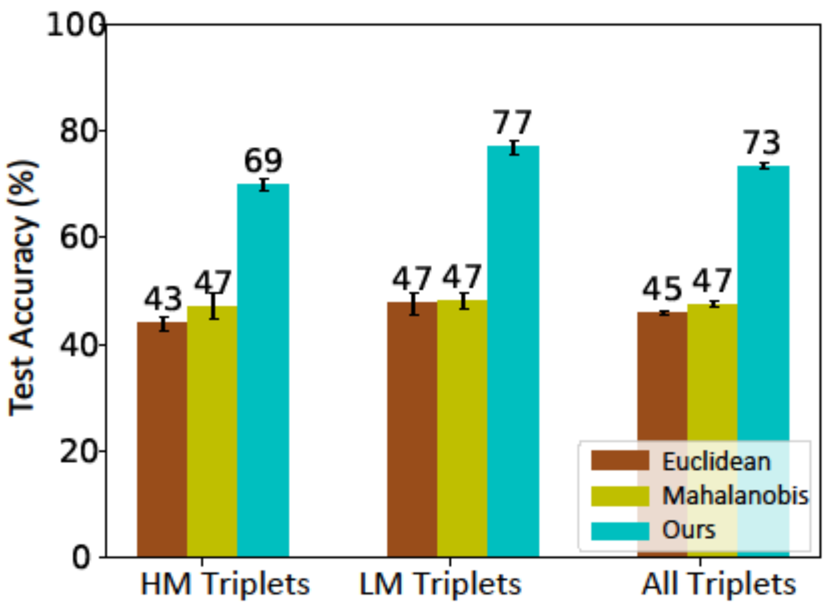
(1) Experimental Results (Held-Out Triplets)

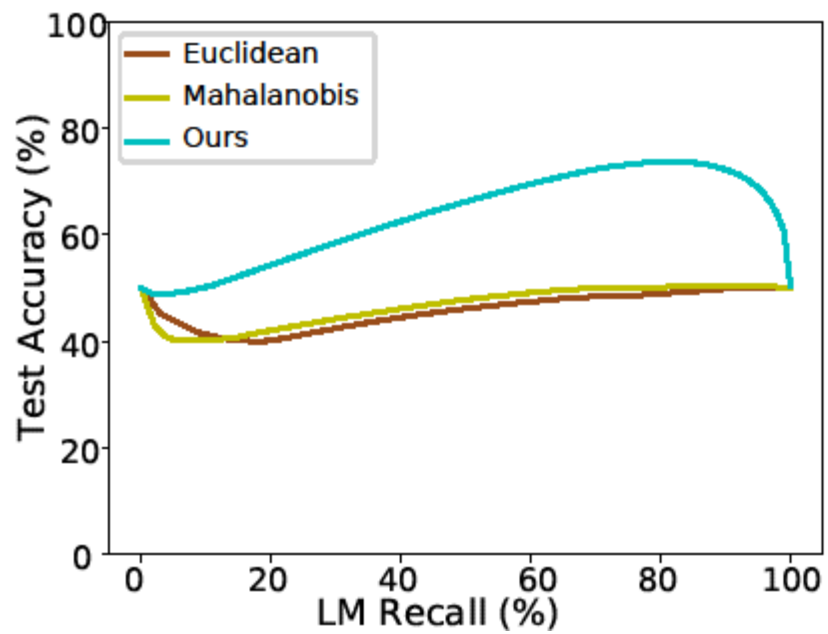




Triplet Generalization Accuracy (TGA) of different metric at optimal threshold (left) and full range of thresholds(right) ξ_ϕ

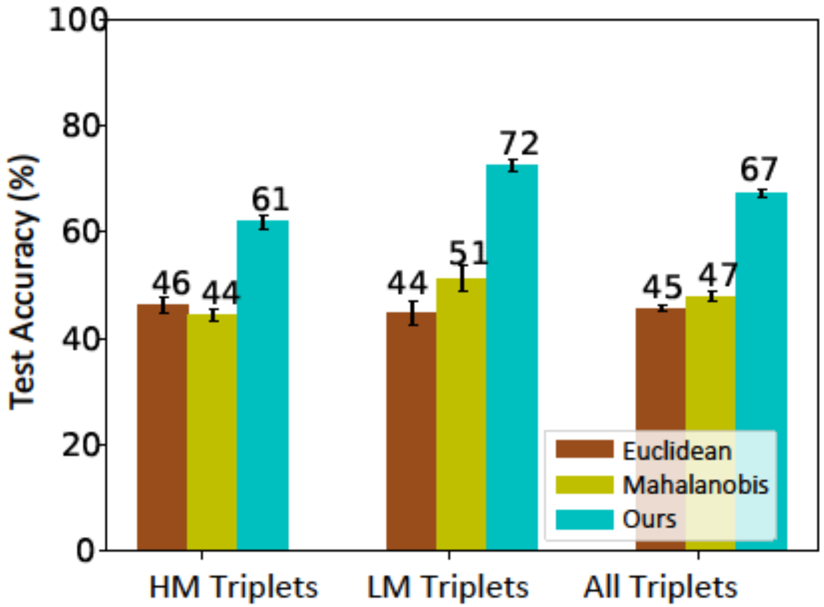
(2) Experimental Results (Held-Out Samples)

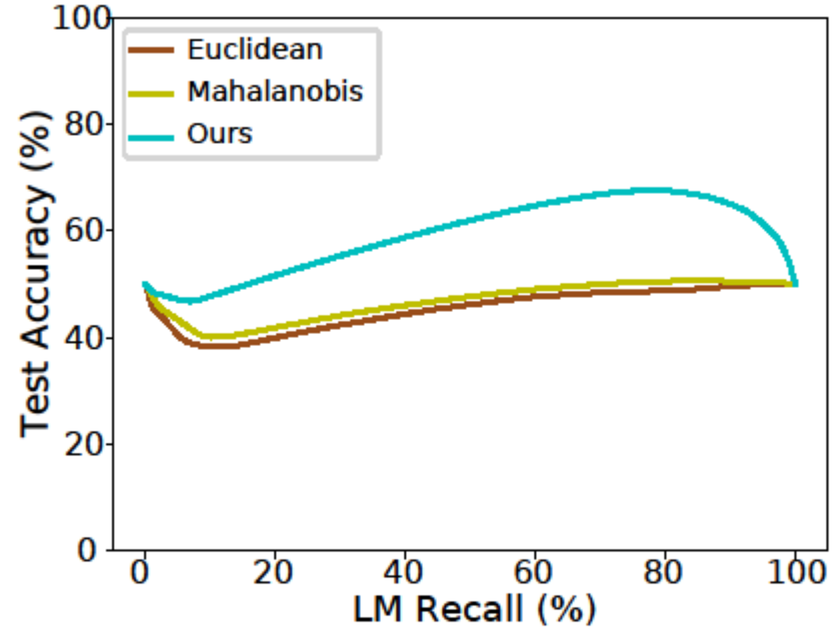




The accuracies of PerceptNet reduces in this harder case (73%), but PerceptNet is still distinctly better

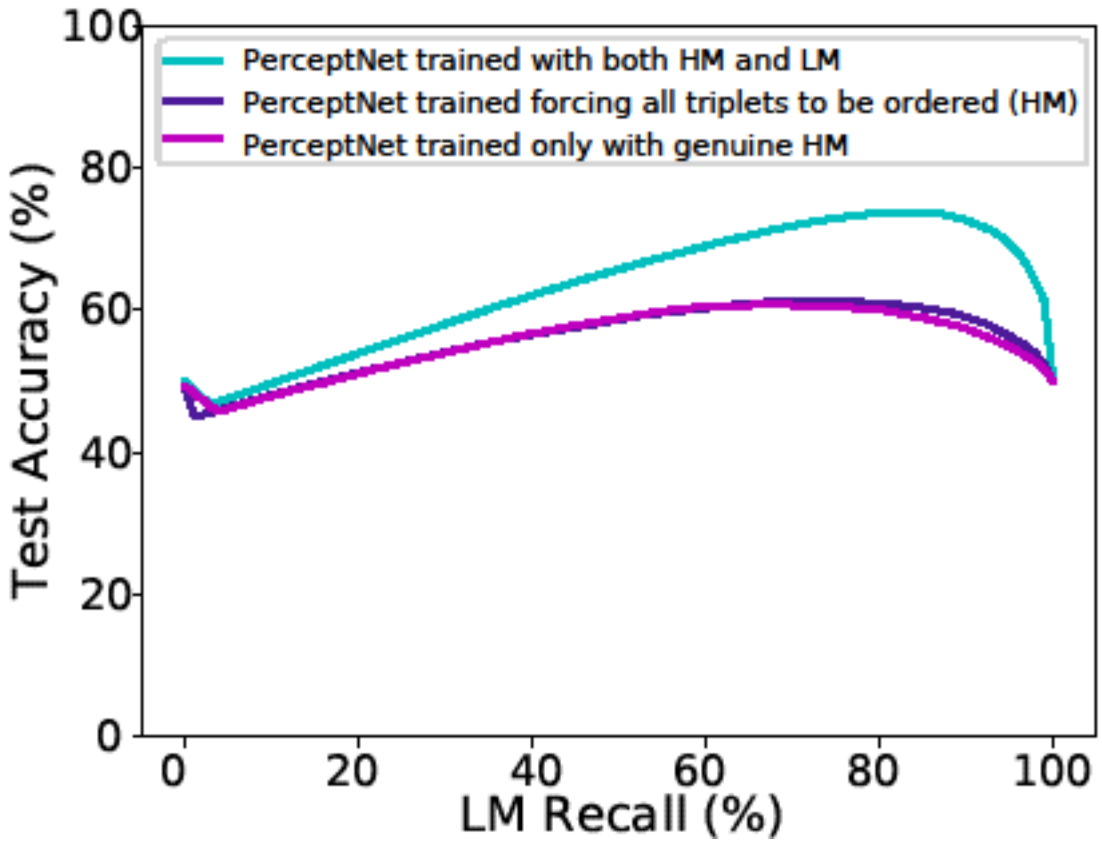
(3) Experimental Results (Held-Out Classes)





The accuracies of PerceptNet further drops to (67%), but PerceptNet is still generalizes much better.

Experimental Results: Importance of low margin triplets



Triplets generation

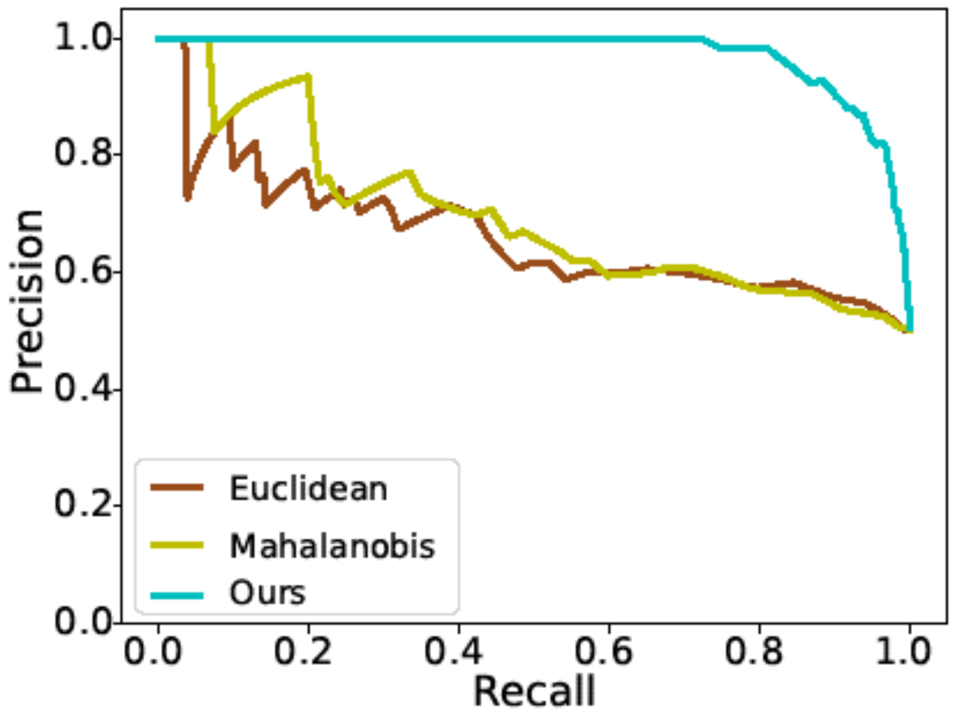
$$H = \{(x_i, x_j, x_k) \mid d^*(x_i, x_k) - d^*(x_i, x_j) \geq \xi^*\}$$

$$L = \{(x_i, x_j, x_k) \mid | d^*(x_i, x_k) - d^*(x_i, x_j) | < \xi^*\}$$

Experimental Results

Pairwise distinguishability of PerceptNet

Ground-truth generation - A pair is considered distinguishable if >50% subjects can distinguish



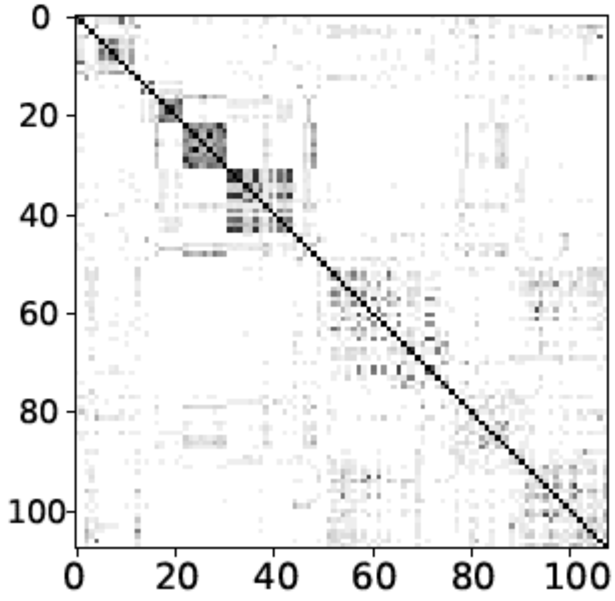
AUC

Perceptnet	0.97
Mahalanobis	0.69
Euclidean	0.66

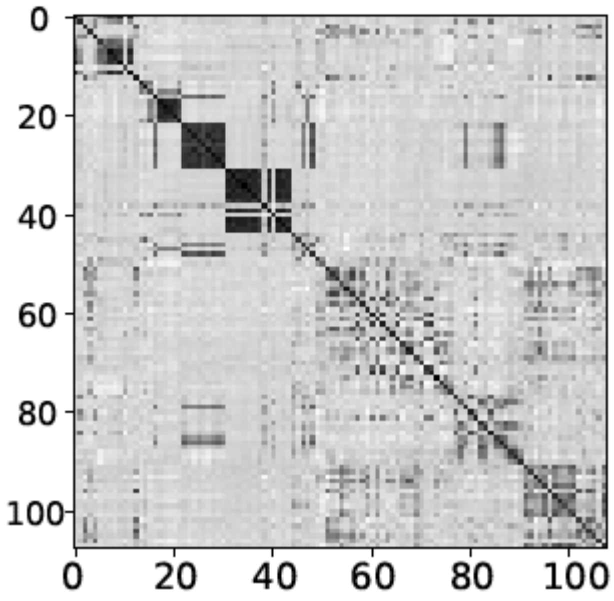
Precision-recall plot for classifying distinguishable and indistinguishable pairs of signals

Experimental Results

Confusion matrix - White indicates low and black high similarity



Ground-truth

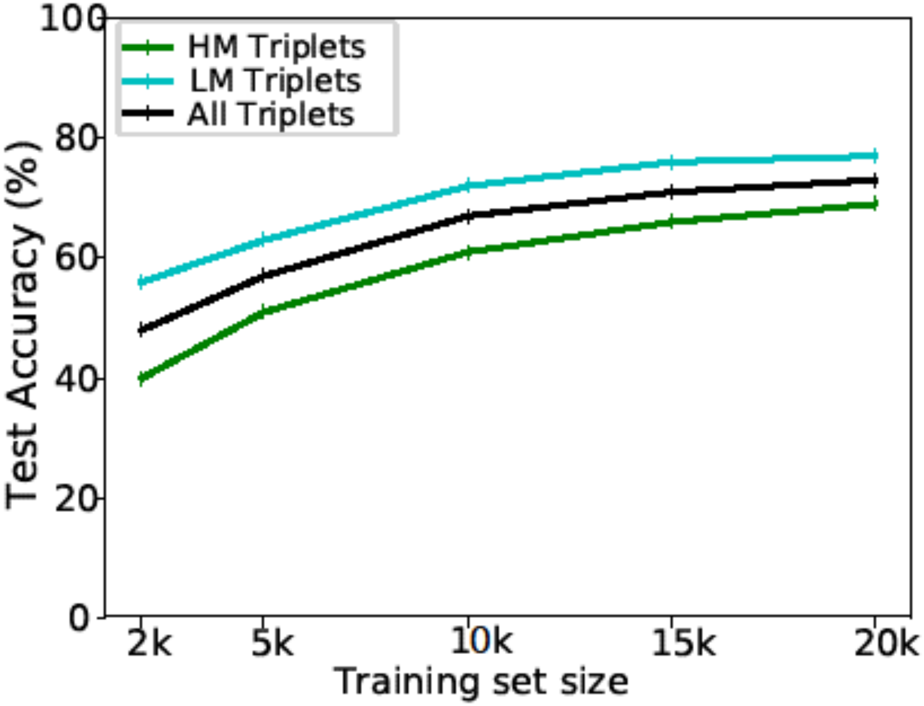


Estimated

PerceptNet is trained only with relative similarity, hence relative ordering is preserved not the numerical ground-truth confusion values

Experimental Results

Dependence of training set size



Accuracy increases proportionally with the size of the training set, but with decreasing benefits for larger sizes

Perceptual Embedding of Olfactory Signals

Experiments

Input: Chemical features (X) and perceptual descriptor of 268 compounds (Octanol, Benzaldehyde, and Hexenel.)

Chemical features : hydrogen bond, molecular weight and heavy atom count etc

Perceptual descriptors: Human subjects rating against odor descriptors such as pungent, fruit, mint and smoke

$d^*(x, y)$ - obtained using cosine similarity

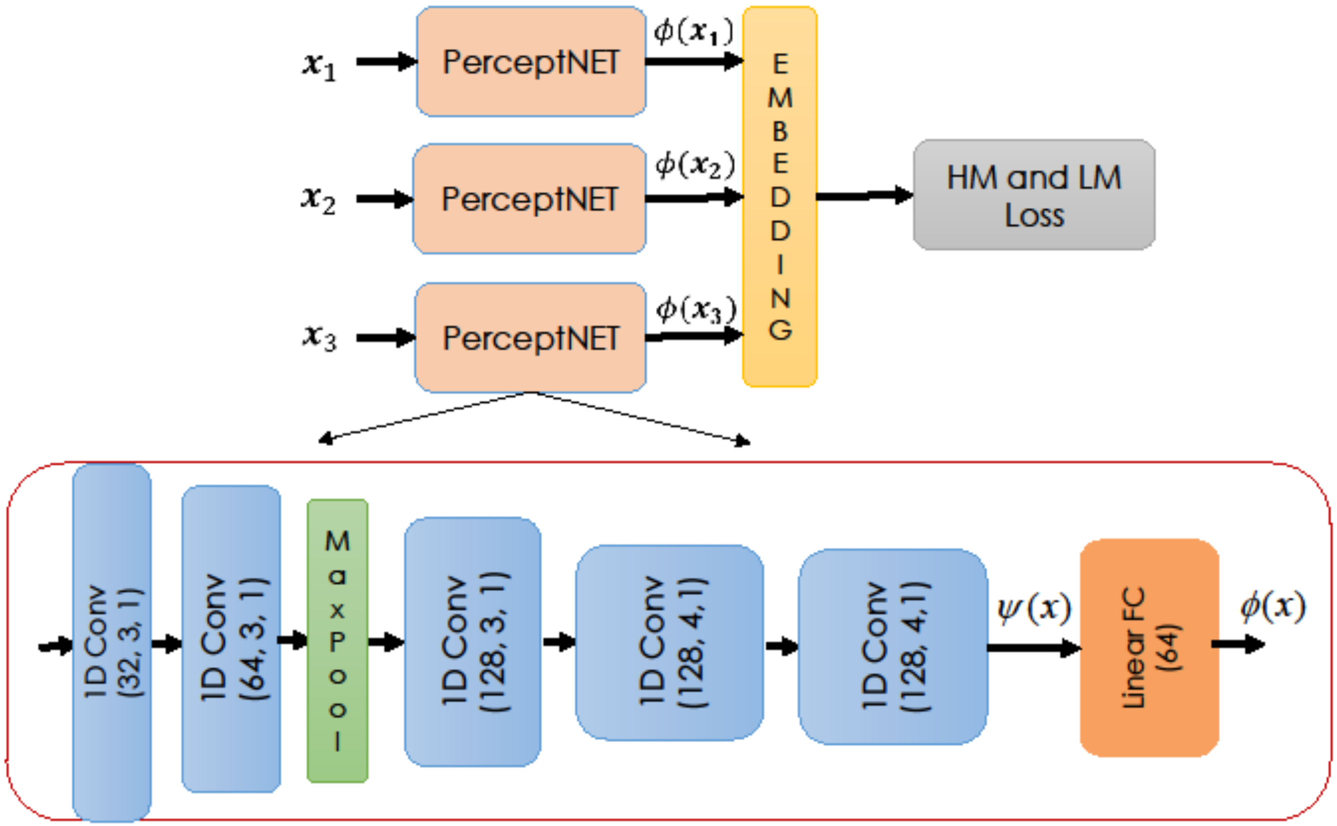
Triplets generation:

$$H = \{(x_i, x_j, x_k) \mid d^*(x_i, x_k) - d^*(x_i, x_j) \geq \xi^*\}$$

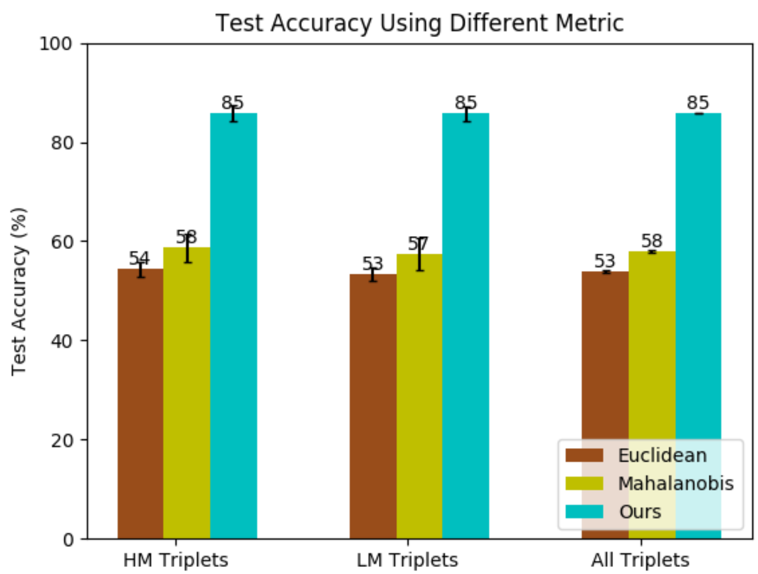
$$L = \{(x_i, x_j, x_k) \mid |d^*(x_i, x_k) - d^*(x_i, x_j)| < \xi^*\}$$

Kush et al. DSP 2016

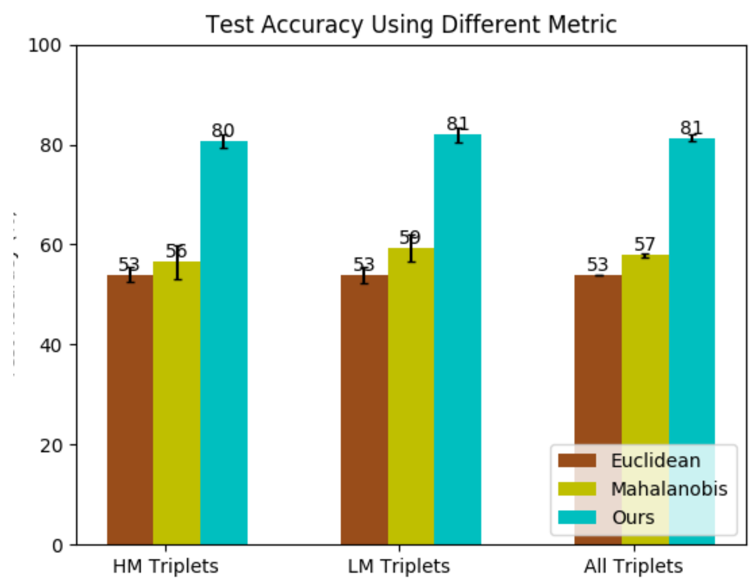
Network Architecture



Experimental Results (Olfactory Data)



Held-Out Triplets



Held-Out Classes

Unlike haptic dataset, in this case, model generalizes quite well even for compounds never seen before

Perceptual Embedding of Image Data

Experiments

Input: 100 images and ground truth perceptual similarity matrix generated from crowd sourced perceptual grouping judgments

Ground-truth:

$d^*(x, y)$ - Fraction of subjects (out of 100) could distinguish between corresponding classes

ξ^* - 10% of the maximum margin over all possible triplets of signal

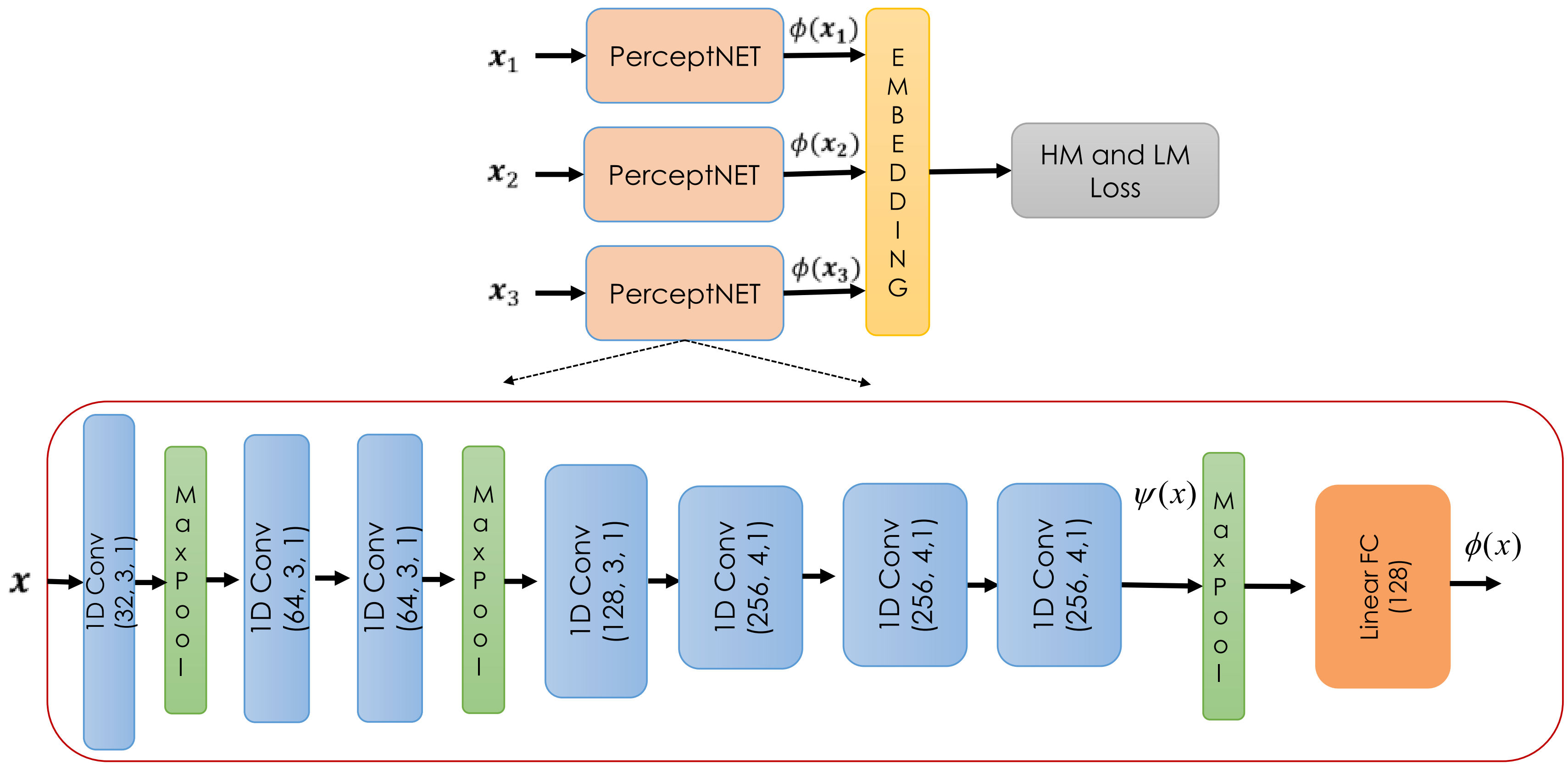
Triplets generation:

$$H = \{(x_i, x_j, x_k) \mid d^*(x_i, x_k) - d^*(x_i, x_j) \geq \xi^*\}$$

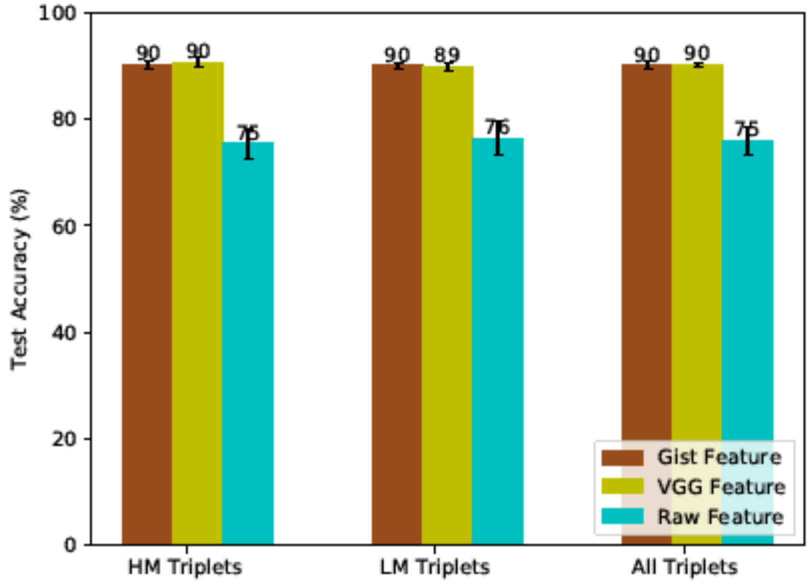
$$L = \{(x_i, x_j, x_k) \mid |d^*(x_i, x_k) - d^*(x_i, x_j)| < \xi^*\}$$

David et al. CHI2015

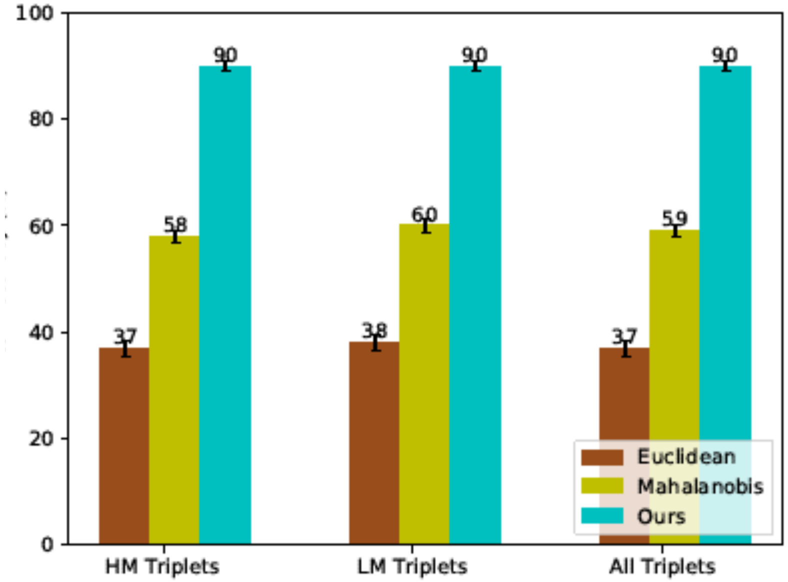
Network Architecture



Experimental Results



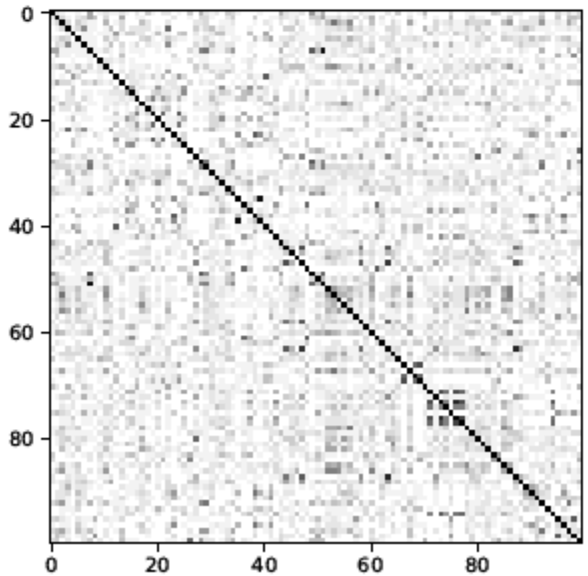
Performance of our model using different features



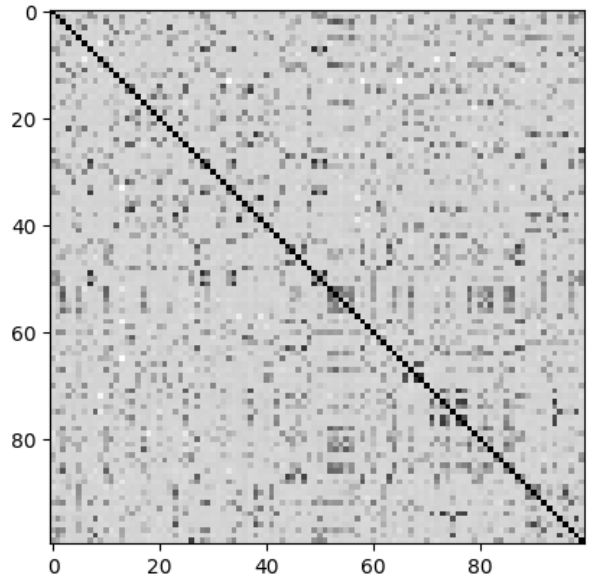
Performance comparison of different metric using gist feature

Experimental Results

Pairwise distinguishability



Ground-truth



Estimated

Confusion matrix- White indicates low and black high similarity

Future Work

- Dealing with limited training data – Active learning
- Generating new sample from perceptual space by inverse mapping
- Better acquisition of data- finding trade-off between human effort and accuracy of model.