Psych 253
Advanced Statistical Modeling

Classification Part 1: Minimum Distance Classifiers

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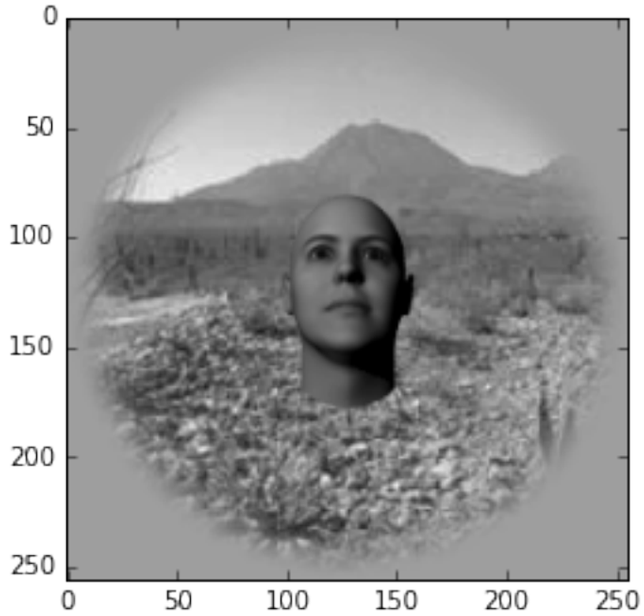
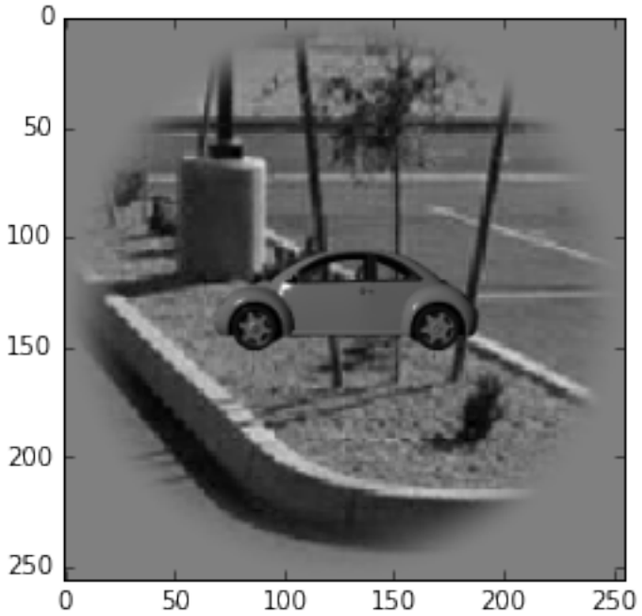
Simple correlations of neurons to stimulus properties





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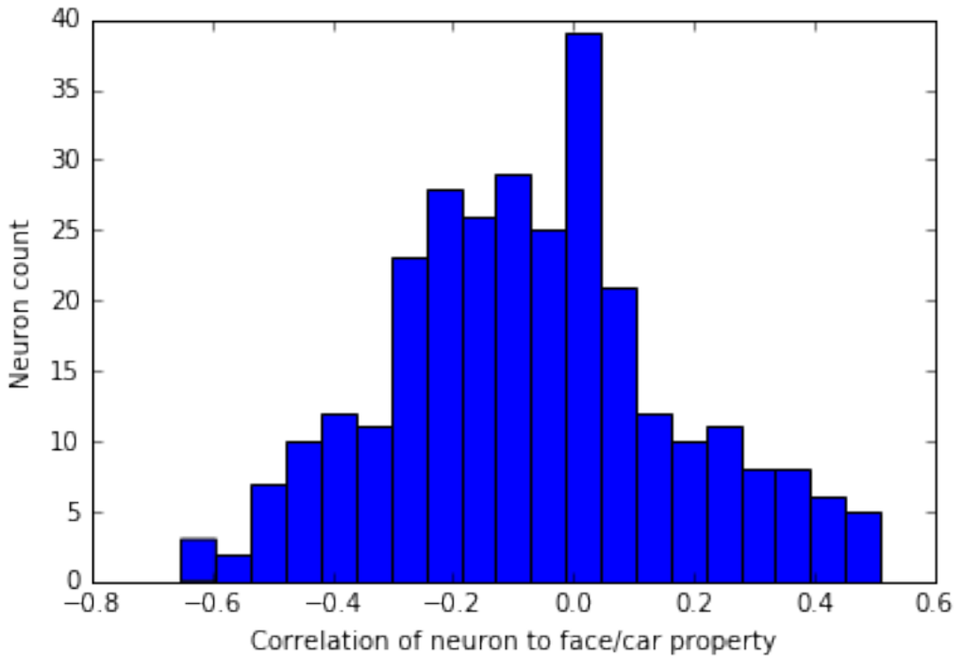

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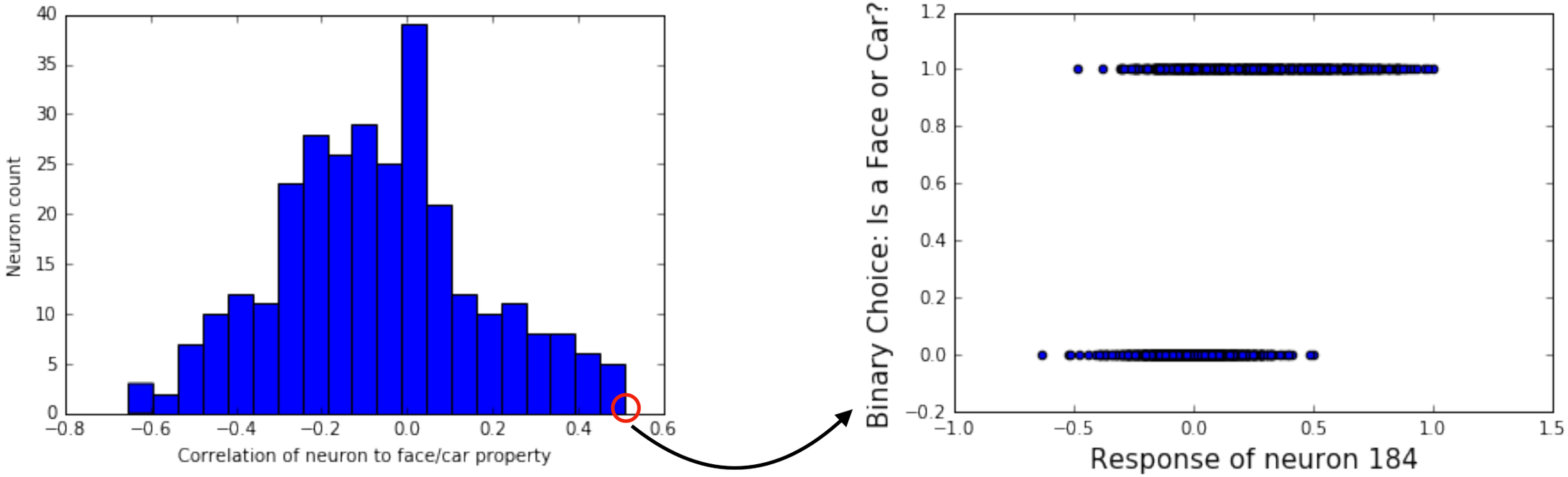

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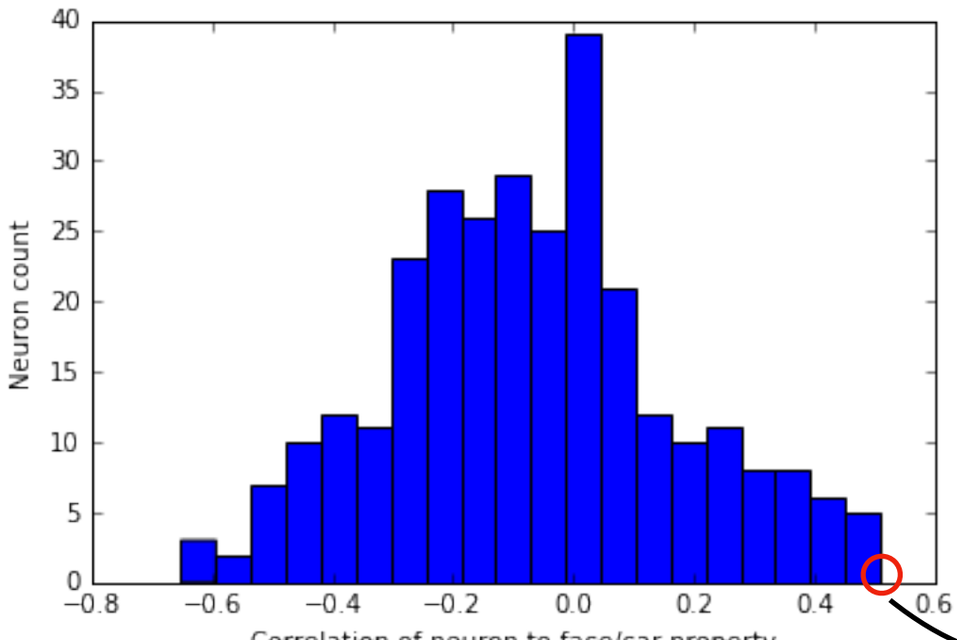

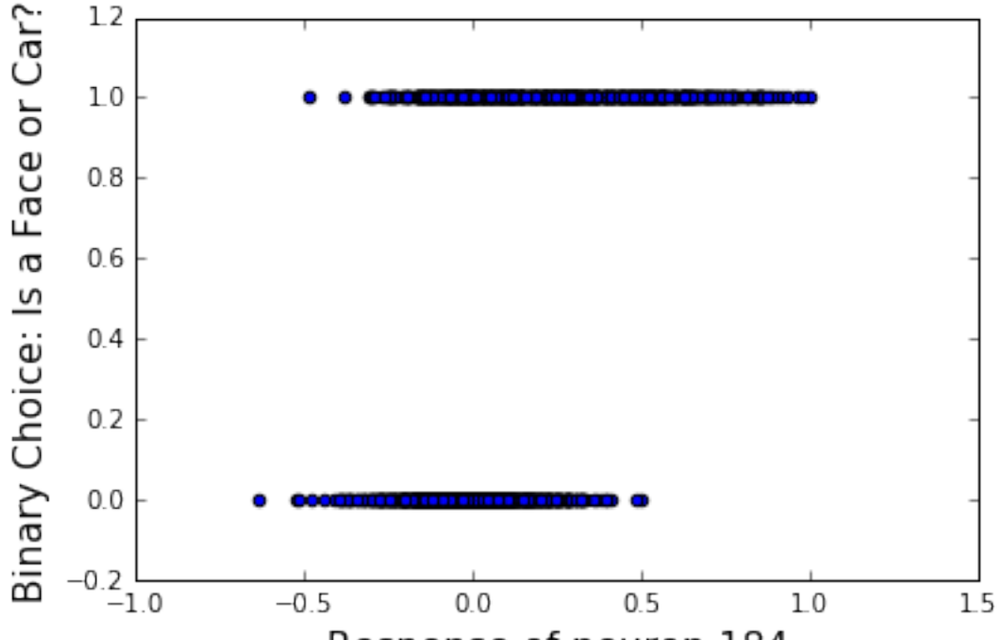

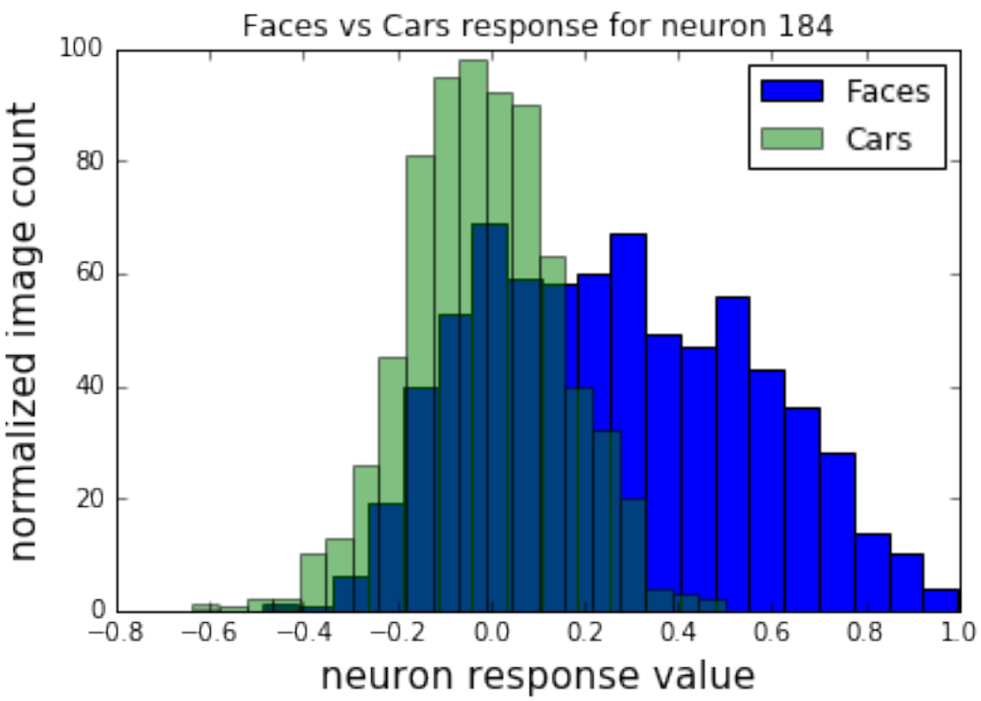

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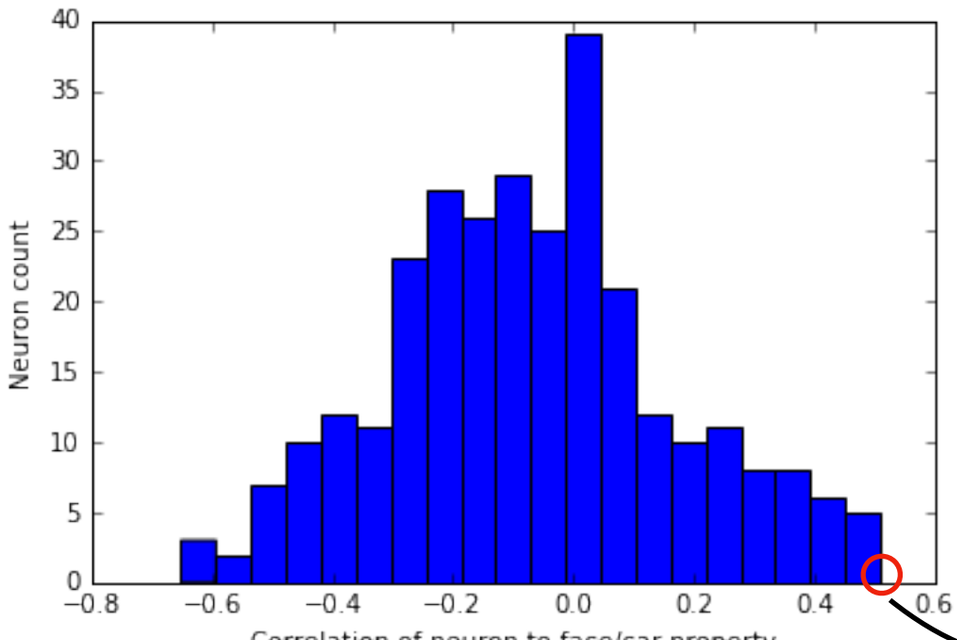

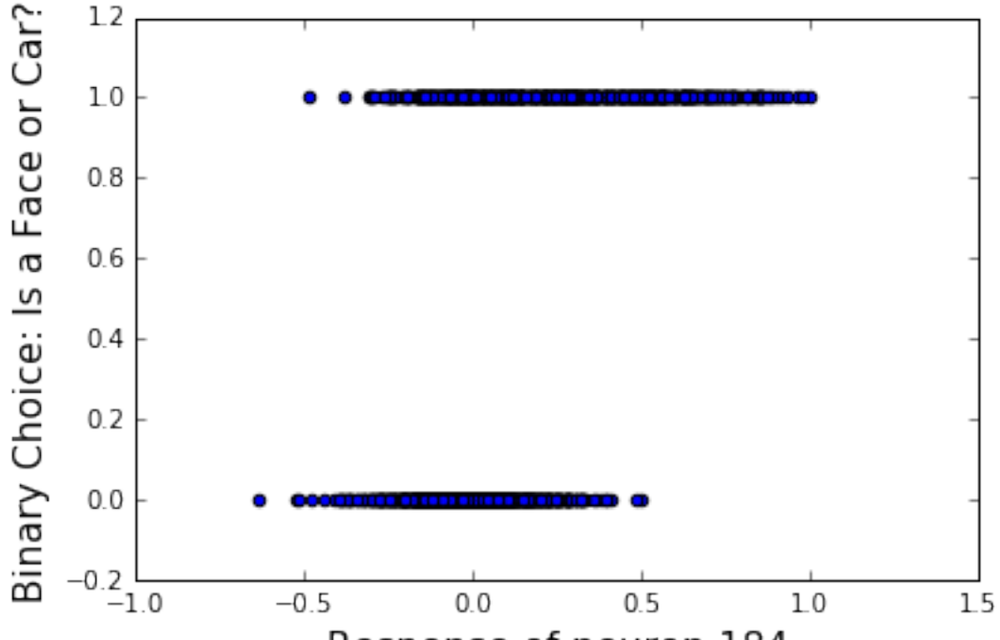

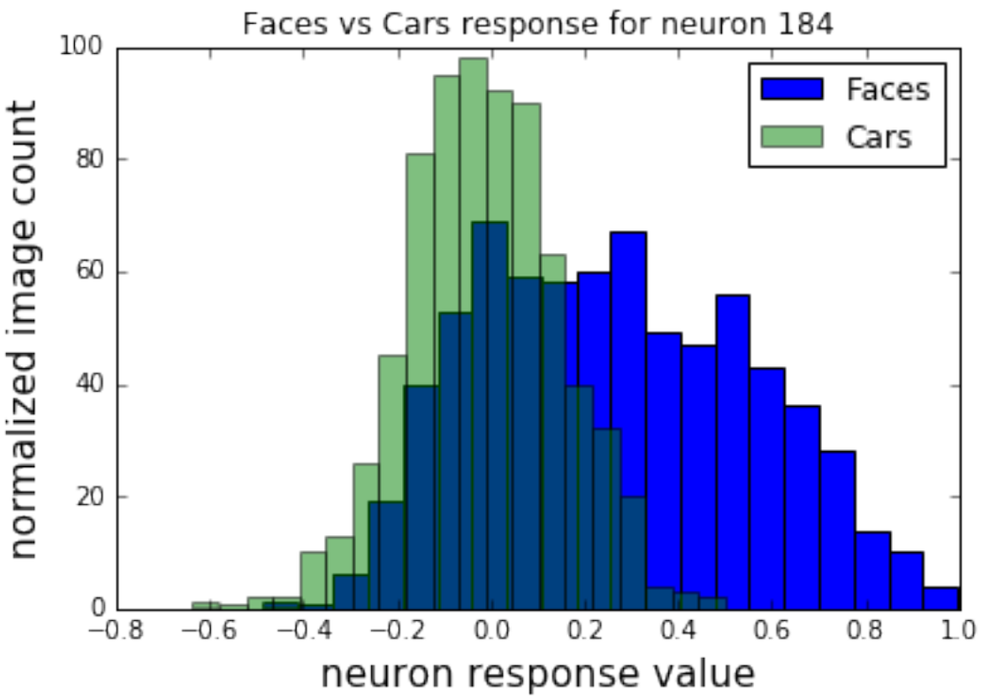

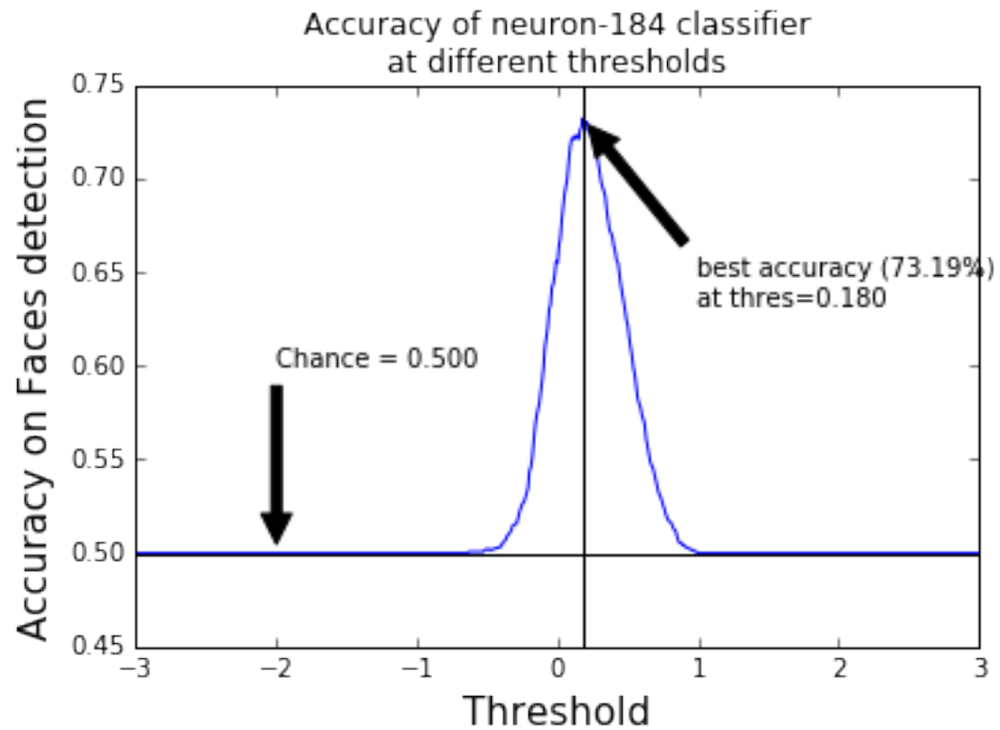

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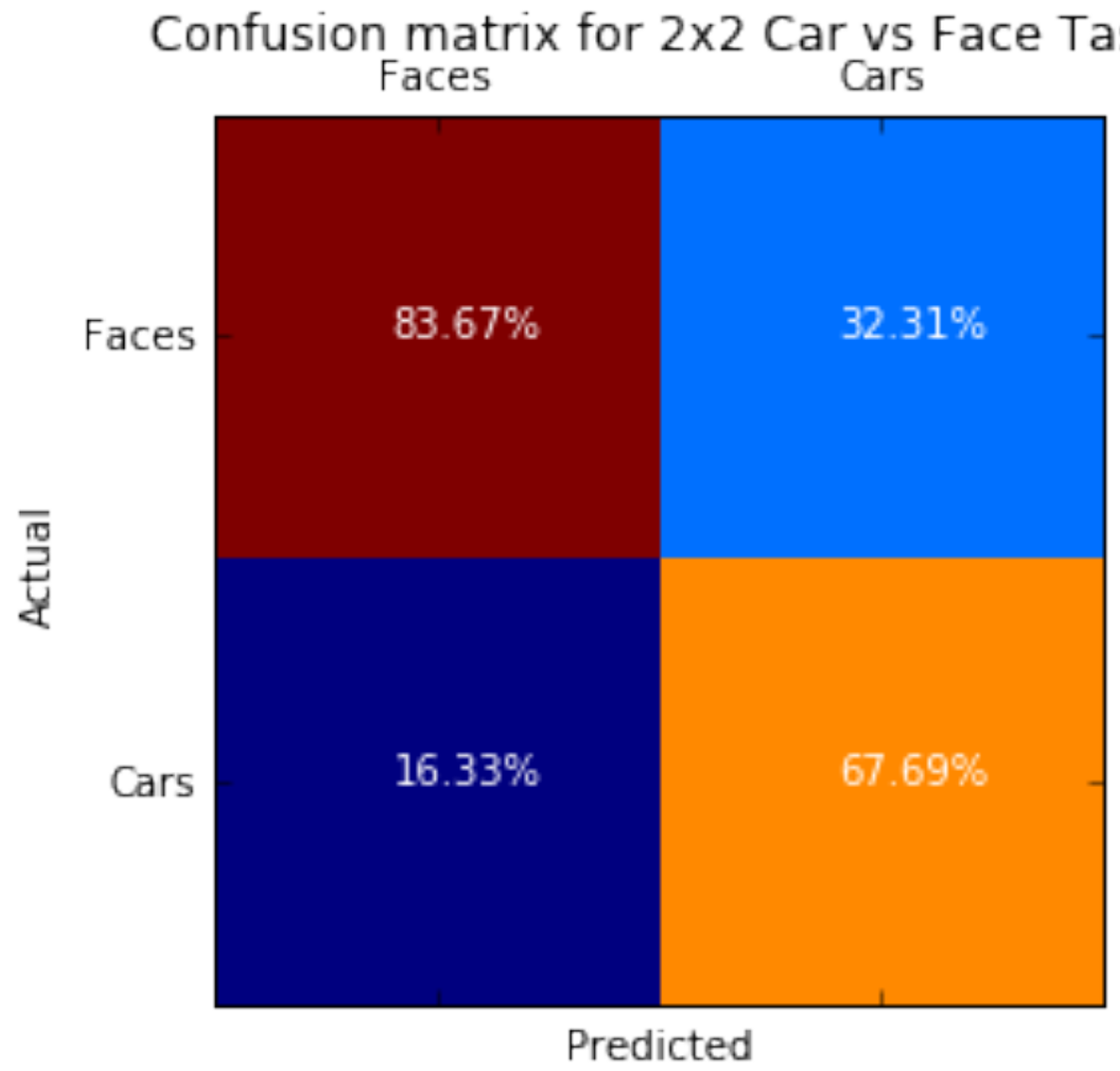
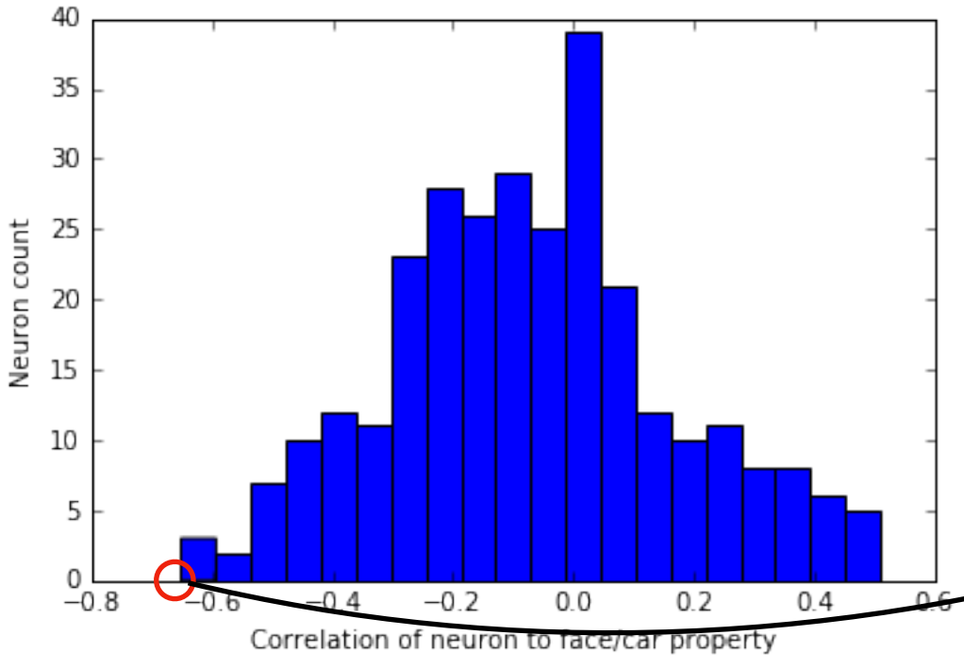
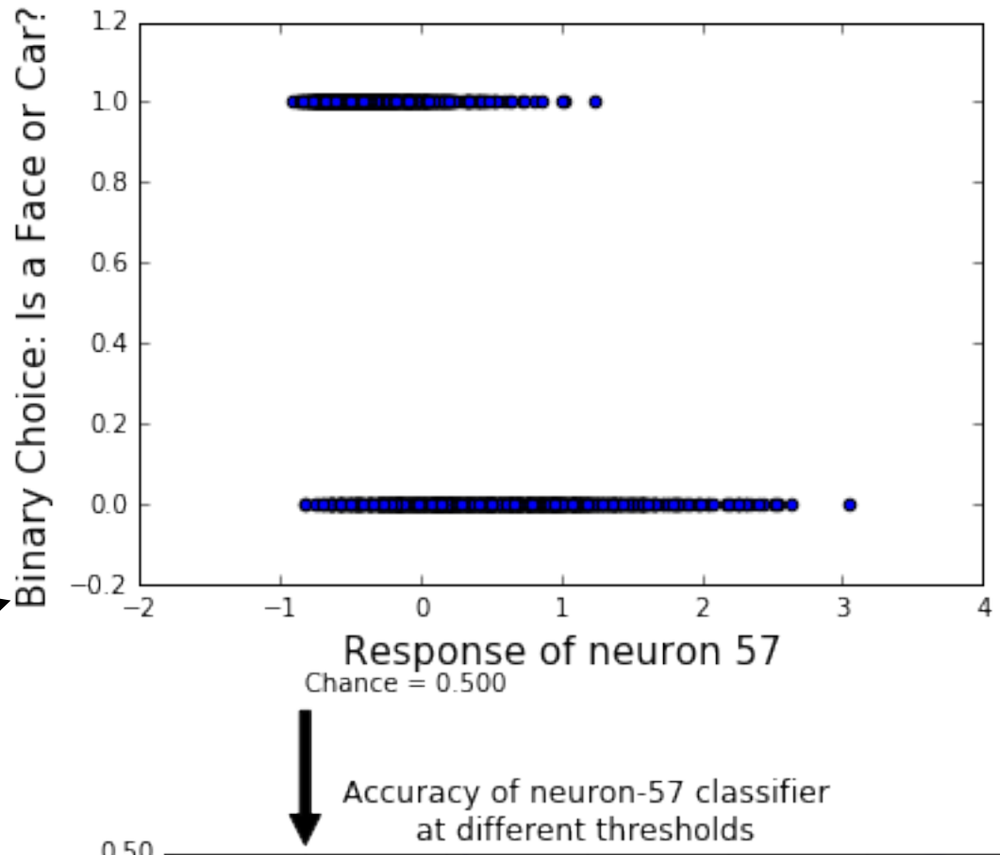
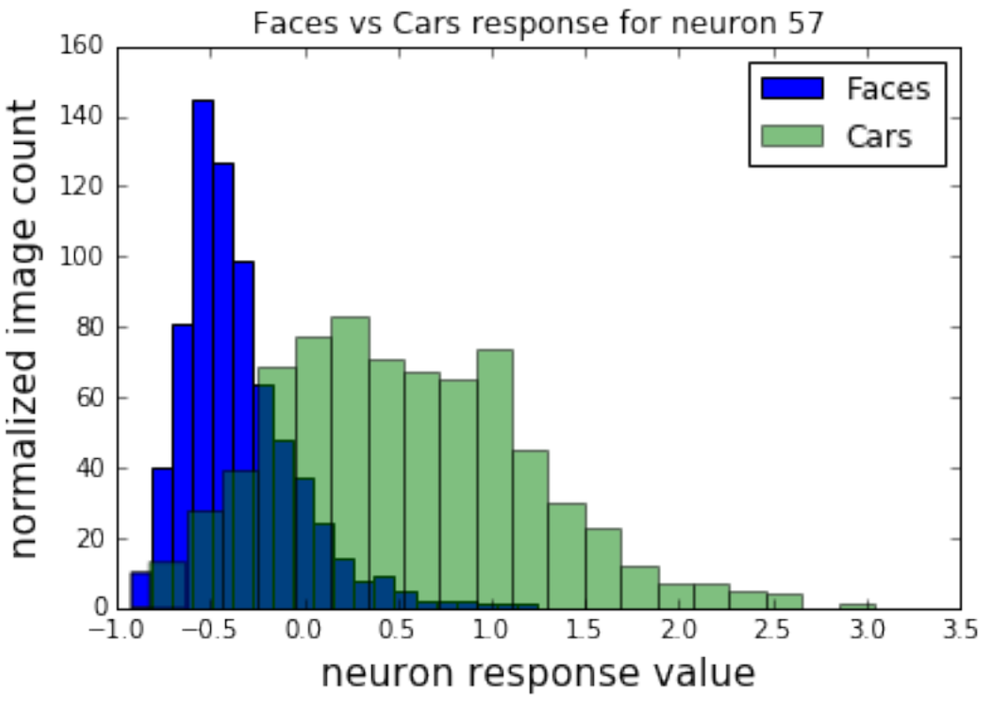


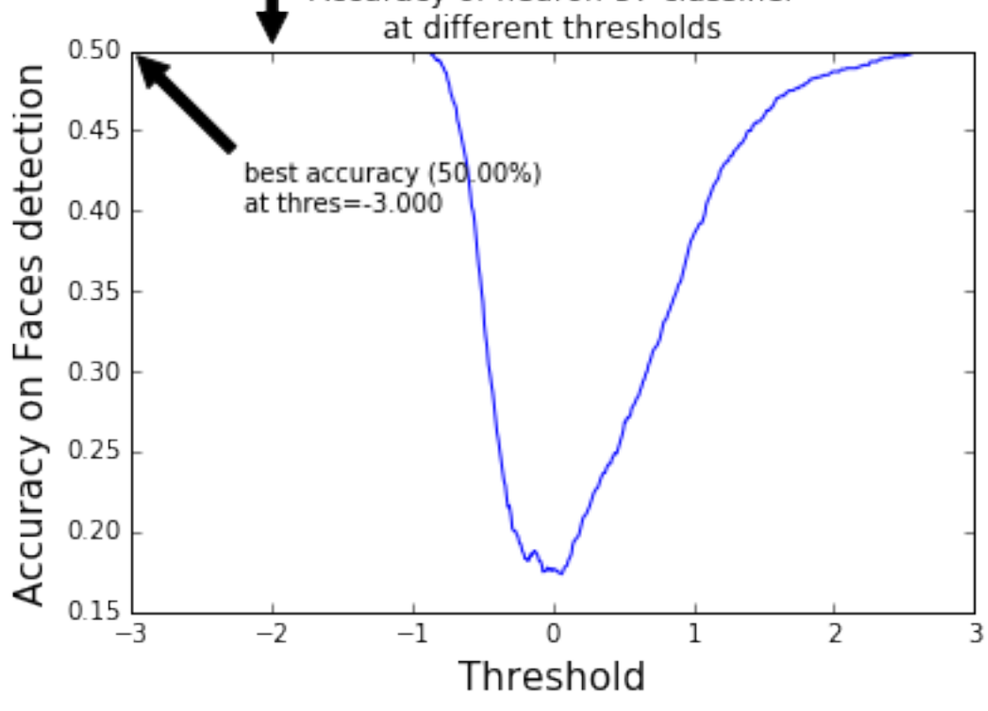
Accuracy = 73.2%

Simple correlations of neurons to stimulus properties

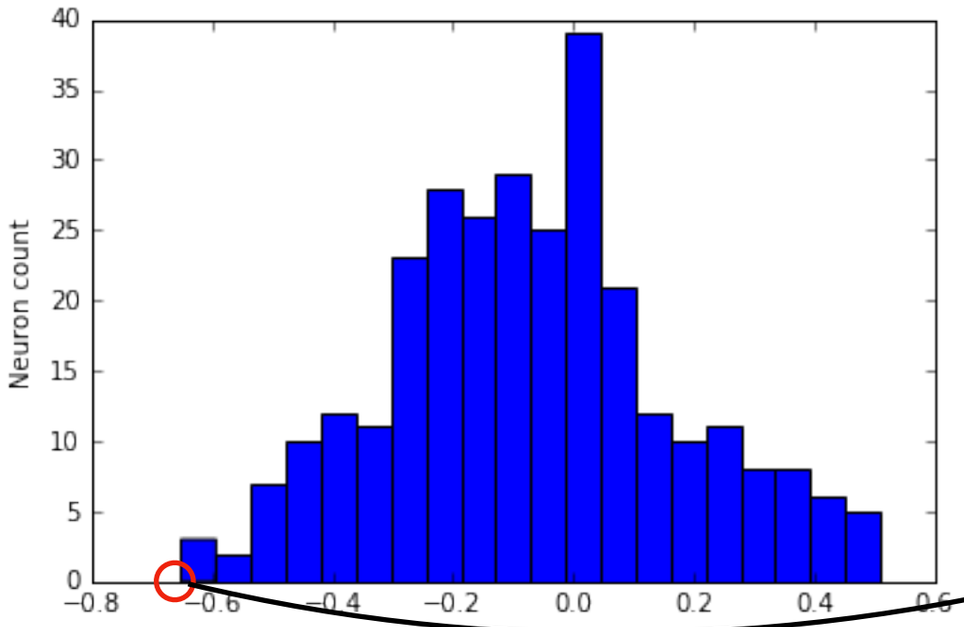


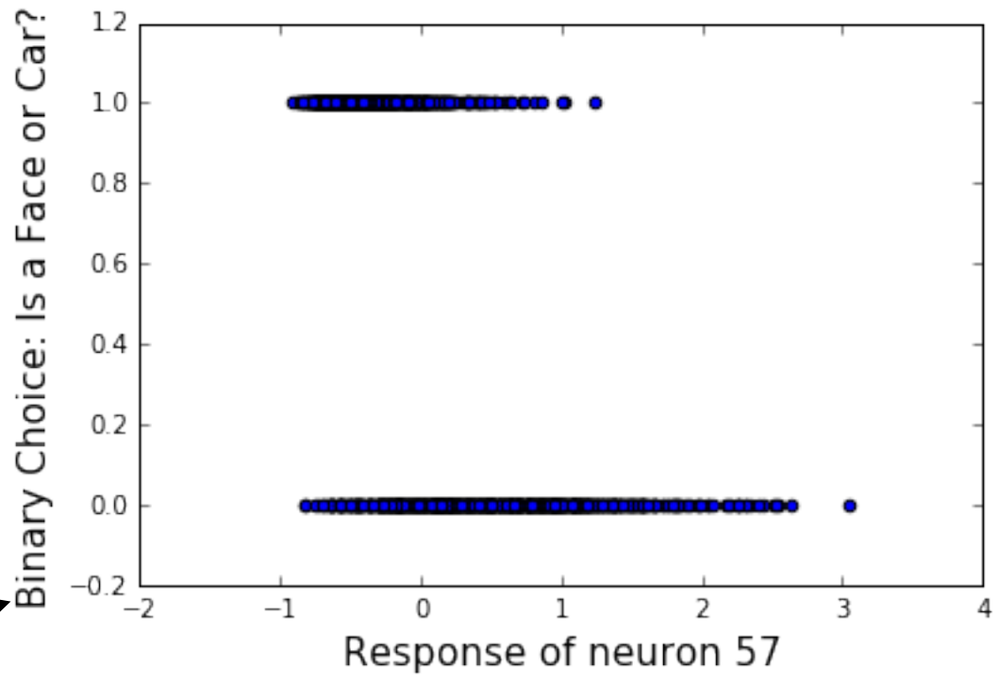


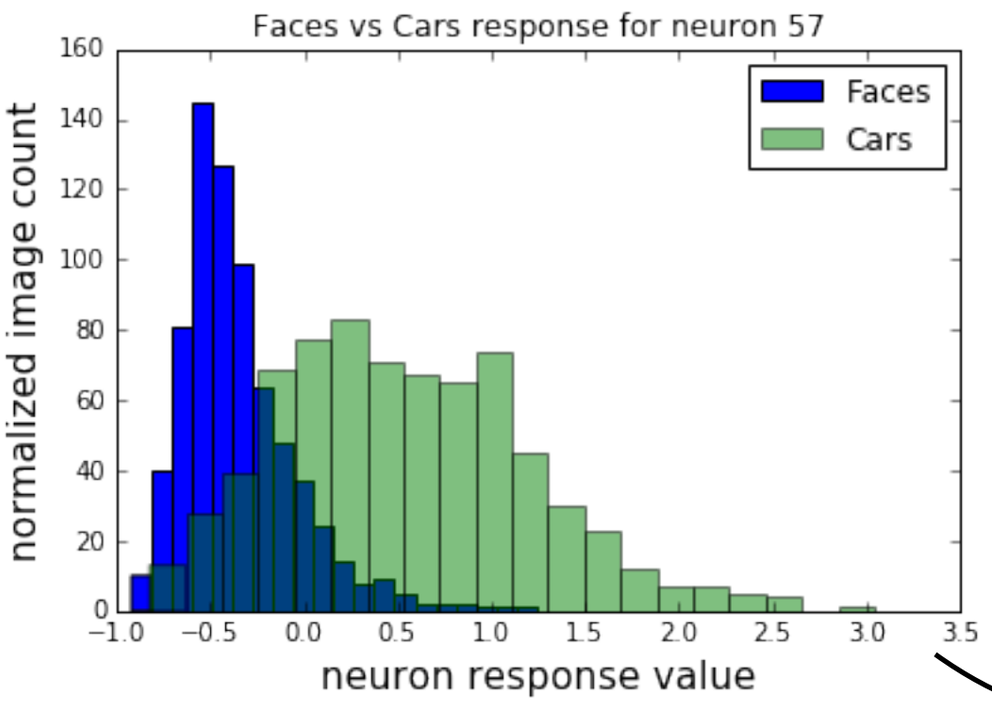




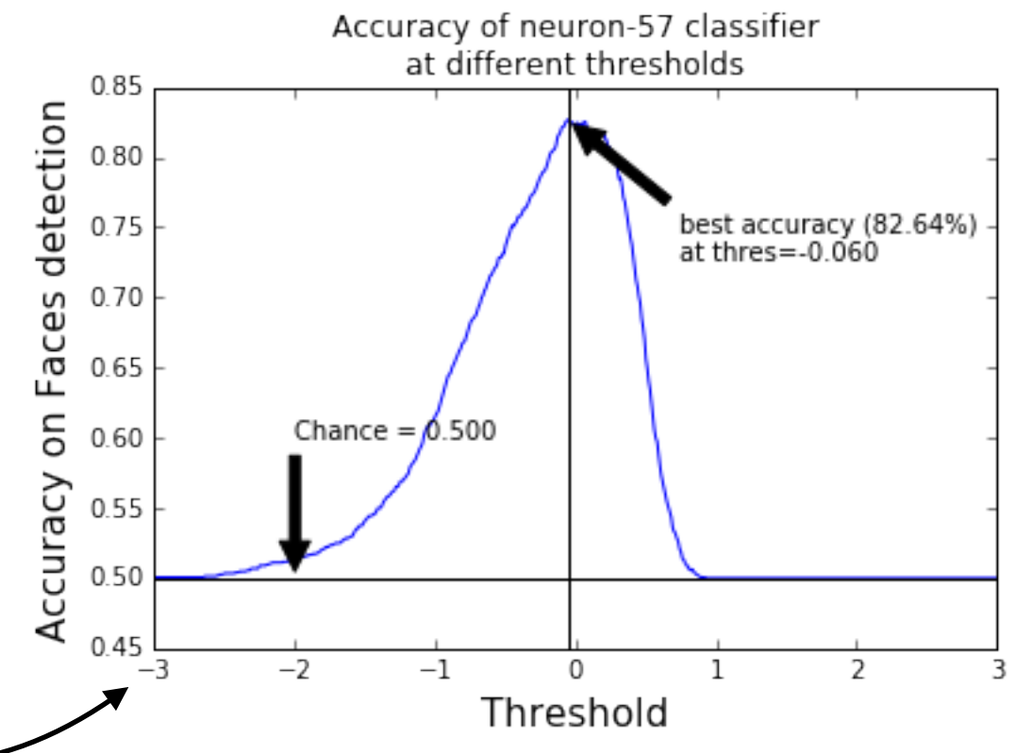
Simple correlations of neurons to stimulus properties



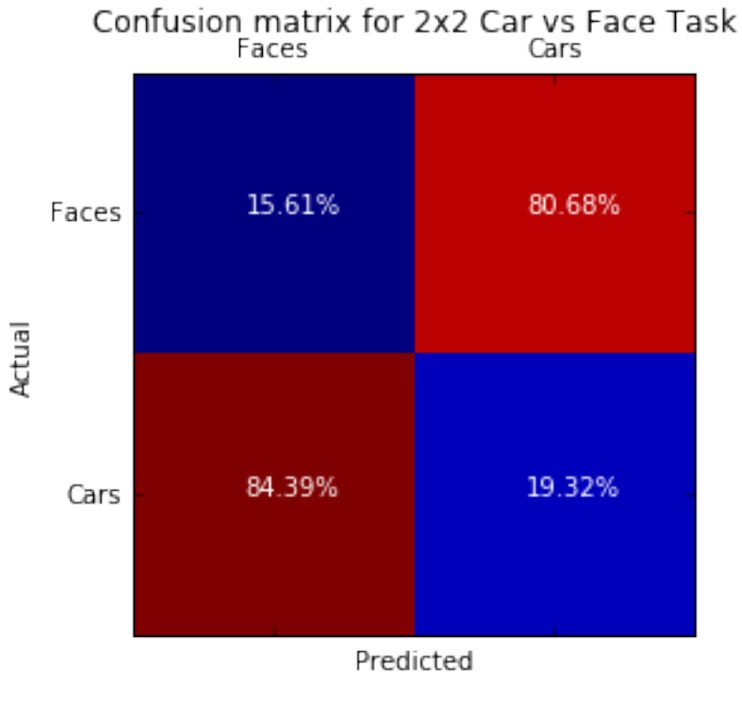


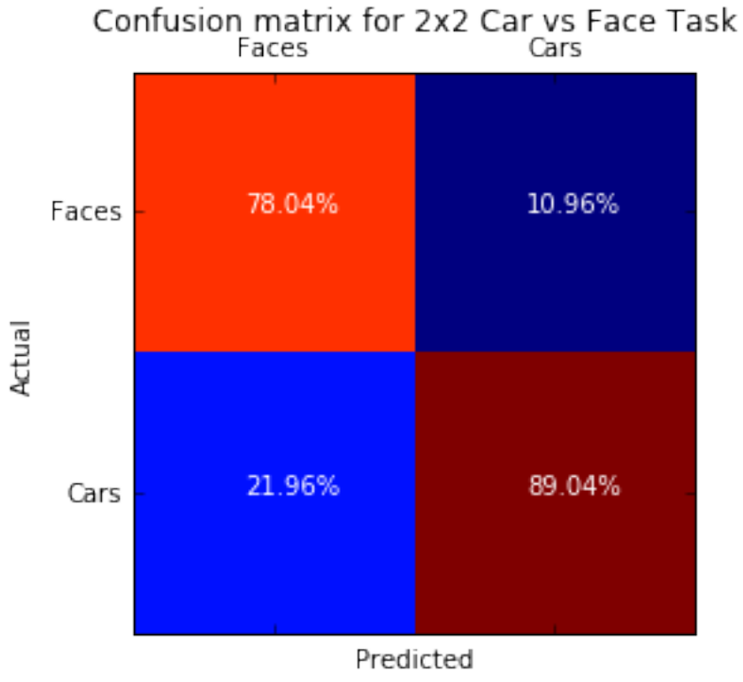


x -1



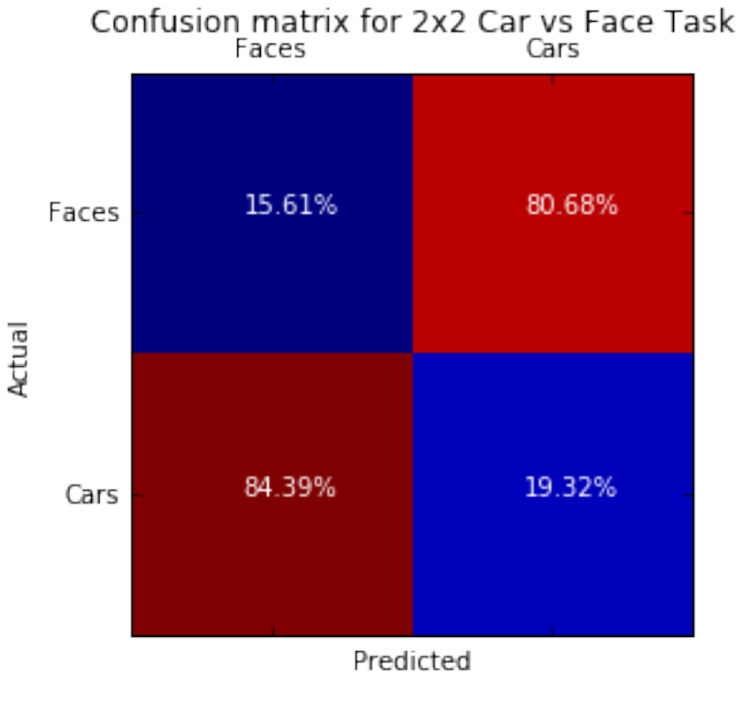
Simple correlations of neurons to stimulus properties

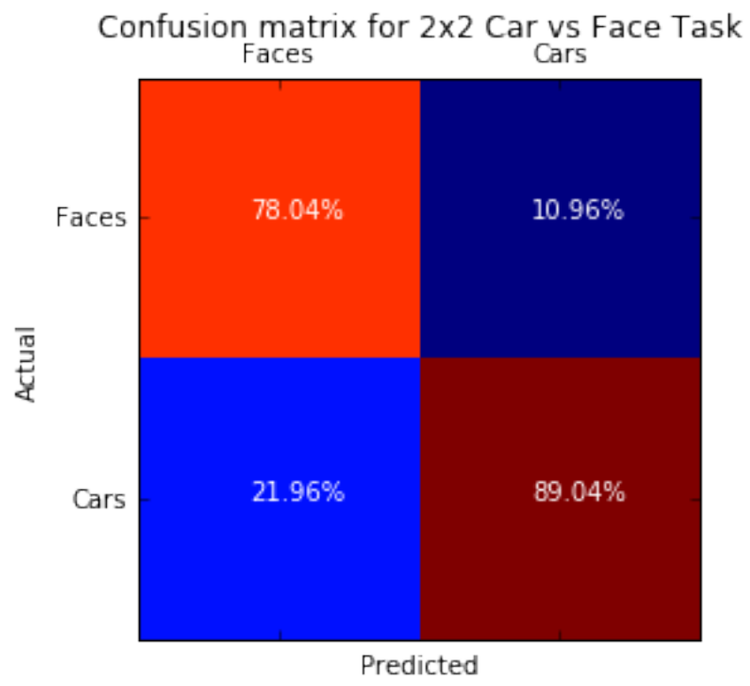




Accuracy = 82.6%

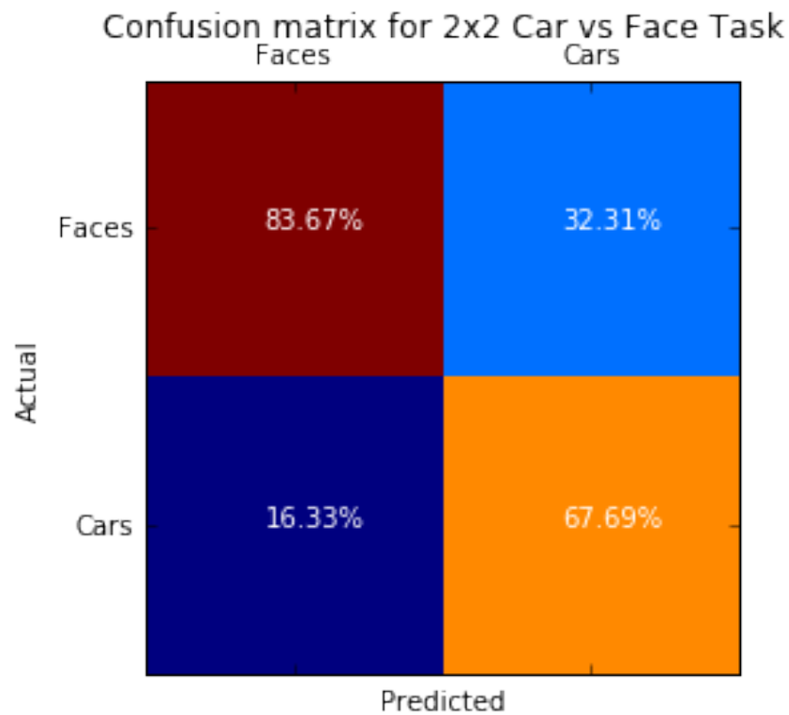
Simple correlations of neurons to stimulus properties





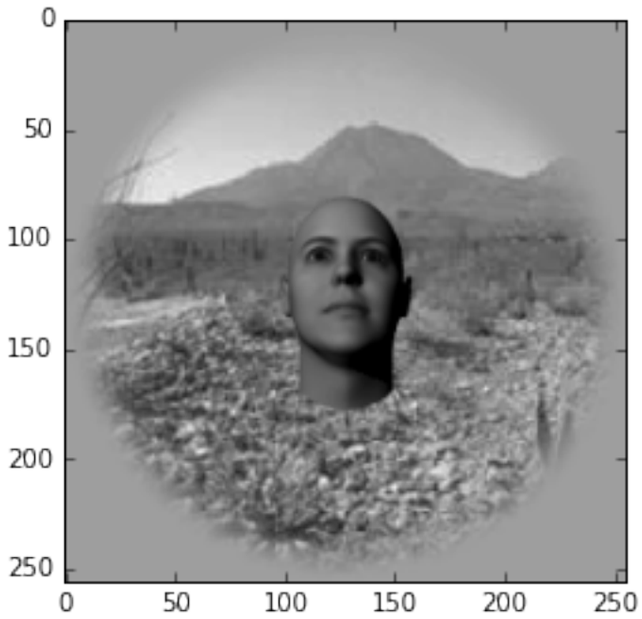
Accuracy = 82.6%

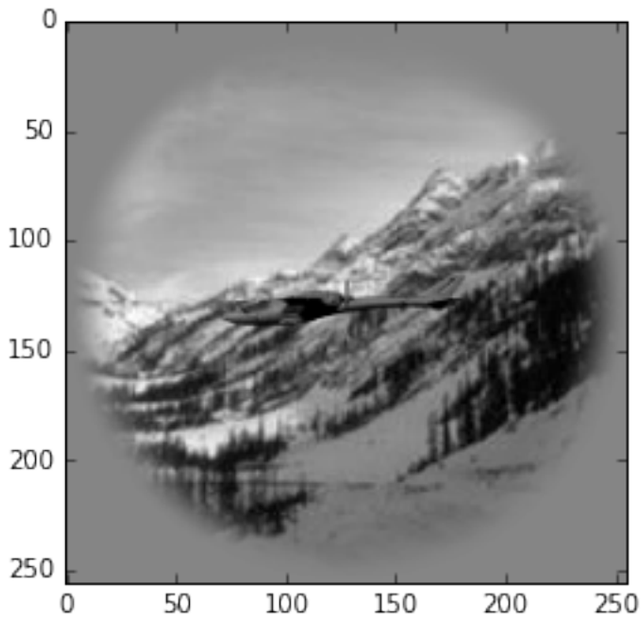
Compare to previous result:

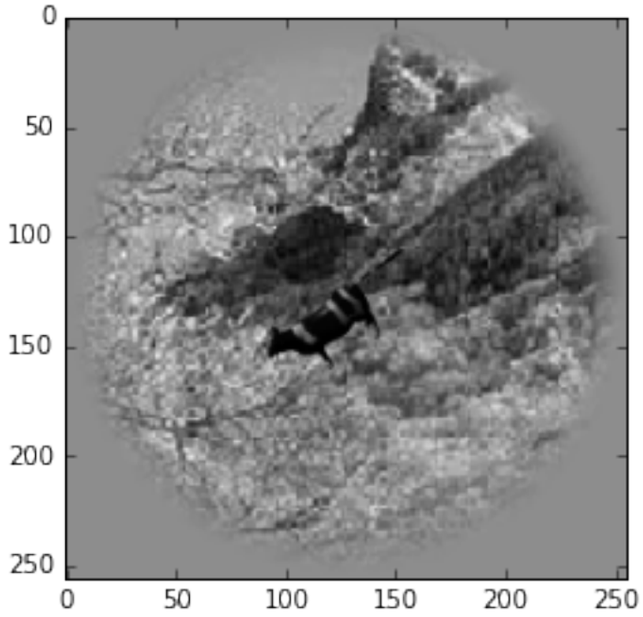


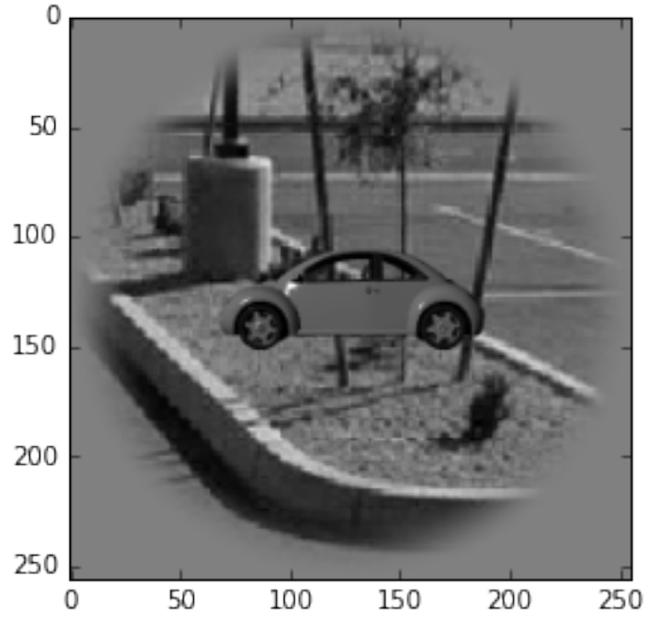
Accuracy = 73.2%

Simple correlations of neurons to stimulus properties









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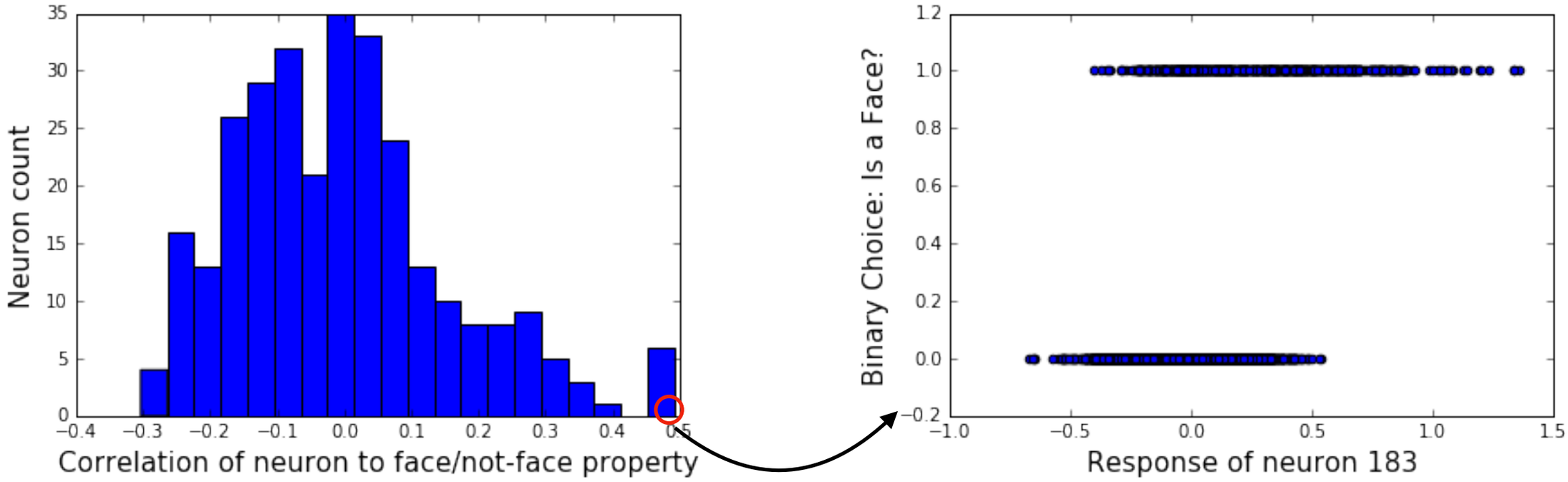
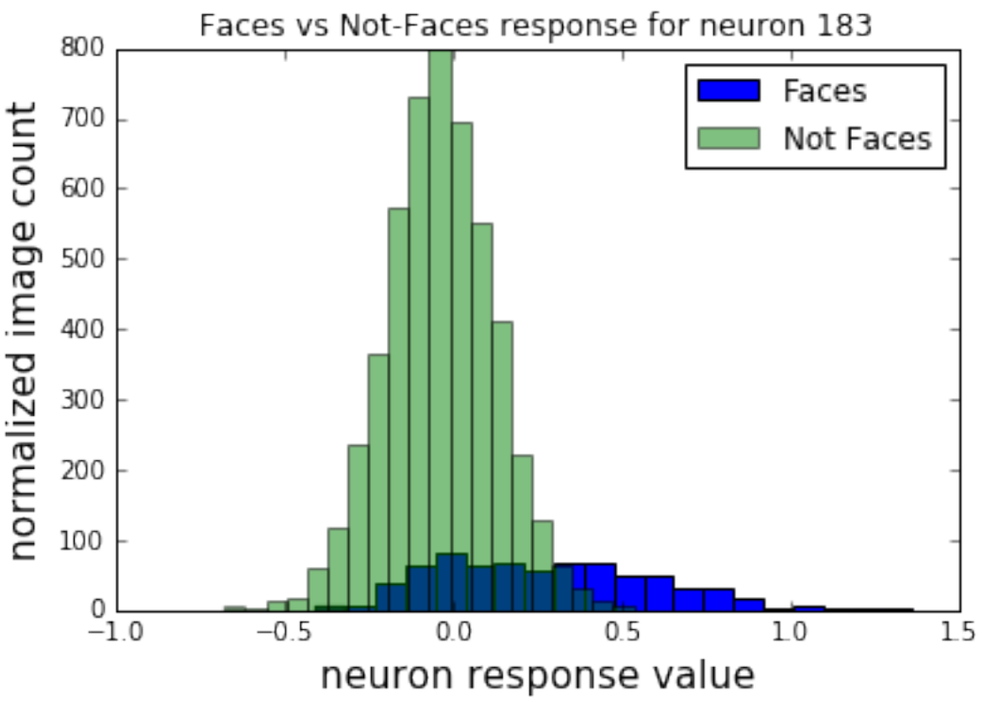
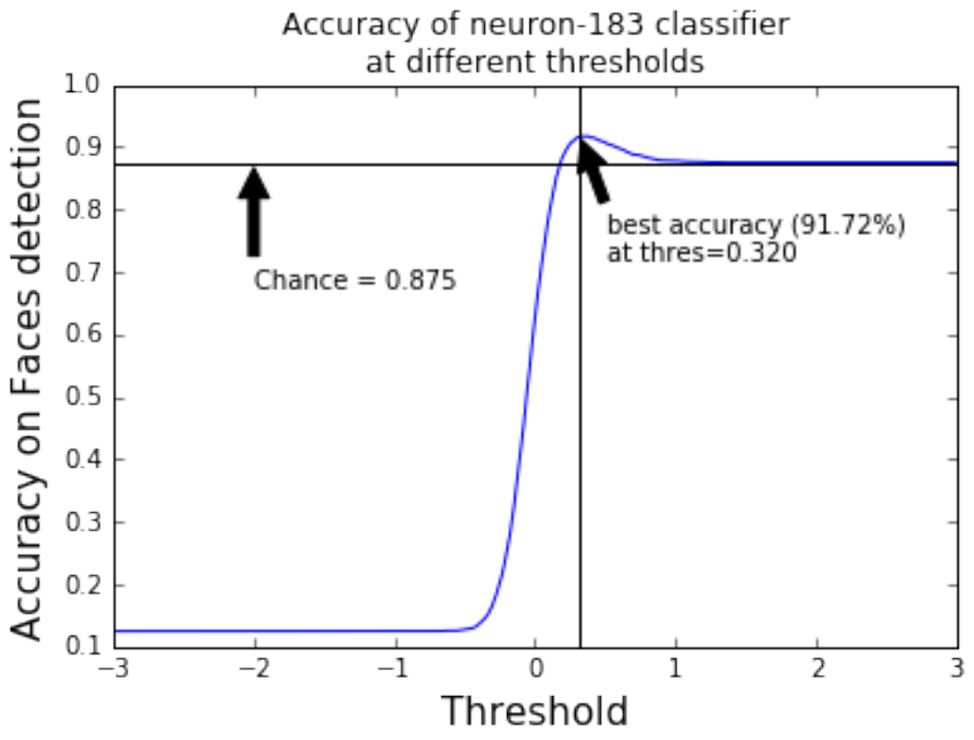
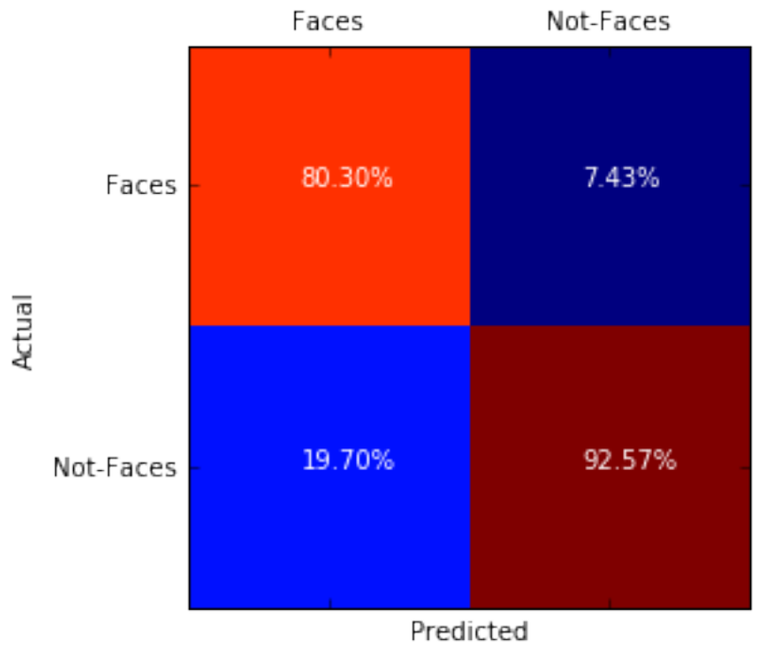






Simple correlations of neurons to stimulus properties

Face-vs-not-face

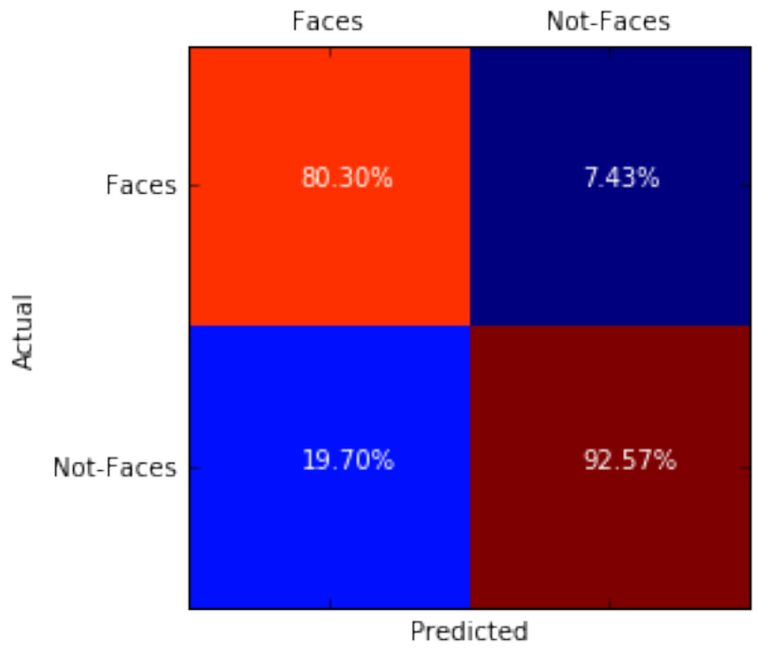


Accuracy = 91.7%

Chance = 87.5%

Simple correlations of neurons to stimulus properties

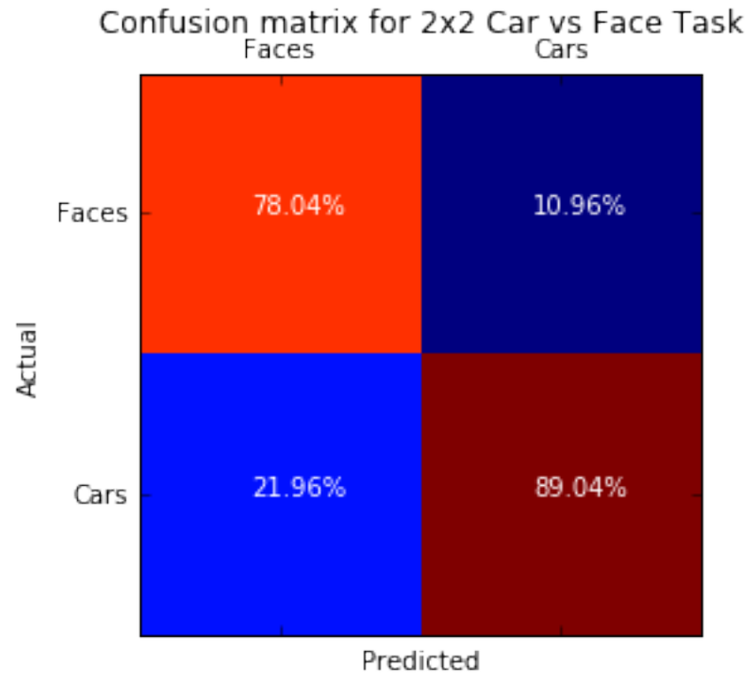
Face-vs-not-face



Accuracy = 91.7%

Chance = 87.5%

Face-vs-car



Accuracy = 82.6%

Chance = 50%

D-prime

$$d' = \frac{\mu_S - \mu_N}{\sqrt{\frac{1}{2}(\sigma_S^2 + \sigma_N^2)}}$$

μ_S = mean of signal μ_N = mean of noise

σ_S = std of signal σ_N = std of noise

D-prime

	Response: Different (*yes*)	Response: Same (*no*)
Stimuli: YES (*different*)	**HIT**	**MISS**
Stimuli: NO (*same*)	**FALSE ALARM**	**CORRECT REJECTION**

$$d' = Z(\text{true positive rate}) - Z(\text{false alarm rate})$$

where

$$Z = (\mathbf{CDF}\ \text{of gaussian})^{-1} = \mathbf{PPF}\ \text{of gaussian}$$

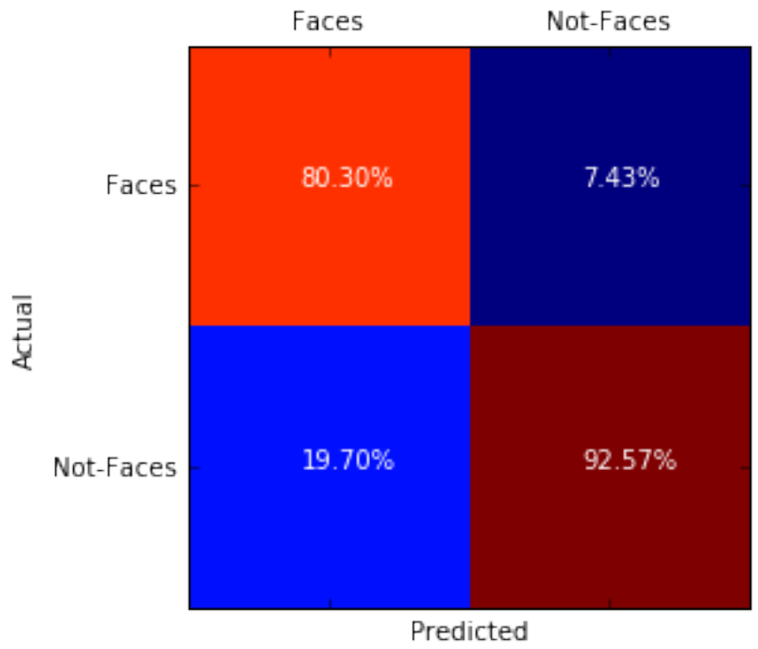
"Z-transform"

Percent-point function

http://phonetics.linguistics.ucla.edu/facilities/statistics/dprime.htm

Simple correlations of neurons to stimulus properties

Face-vs-not-face

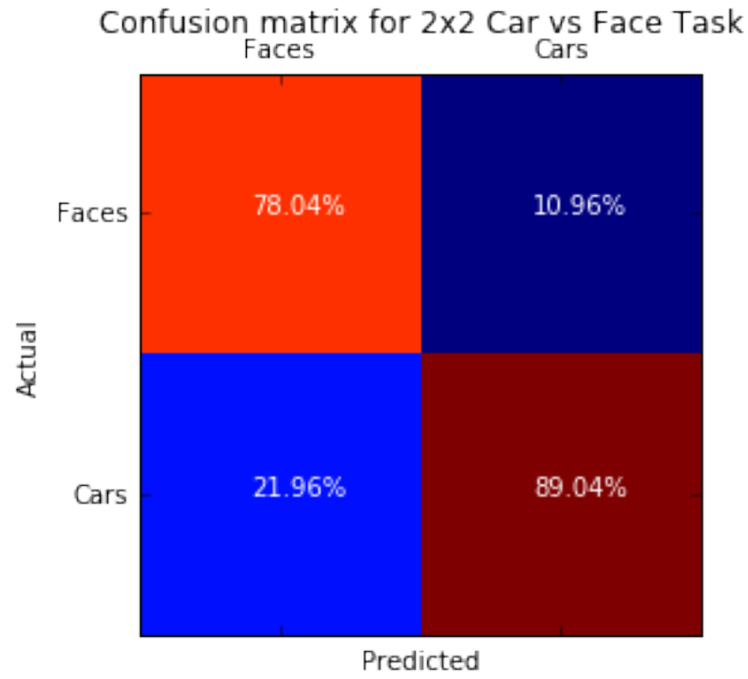


Accuracy = 91.7%

Chance = 87.5%

D-prime = 2.02

Face-vs-car



Accuracy = 82.6%

Chance = 50%

D-prime = 1.998

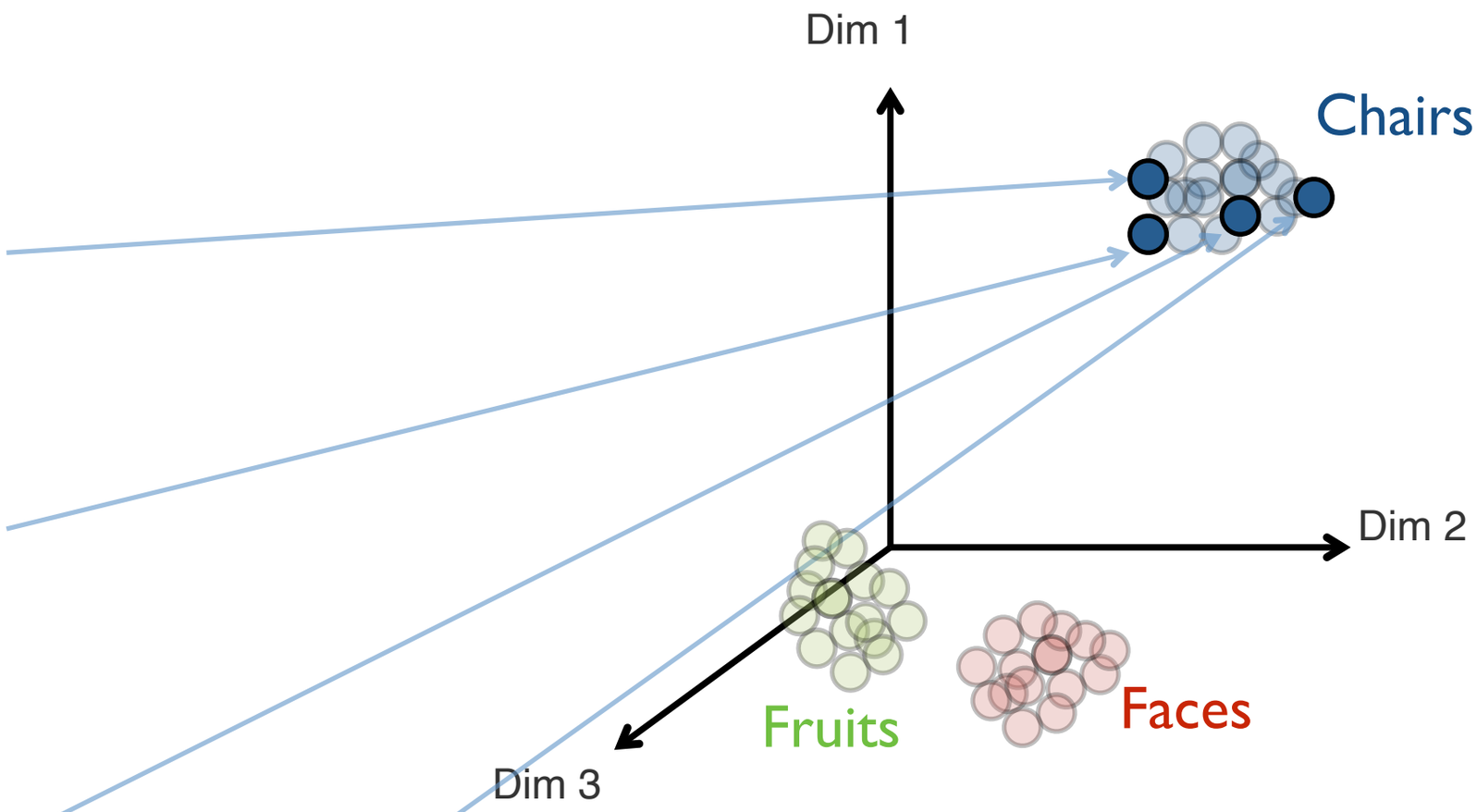
Minimum Distance Classifiers

Minimum Distance Classifiers

Pixel space: $R^{\sim 1000000}$

IT feature space: $R^{4000(?)}$

CHAIRS



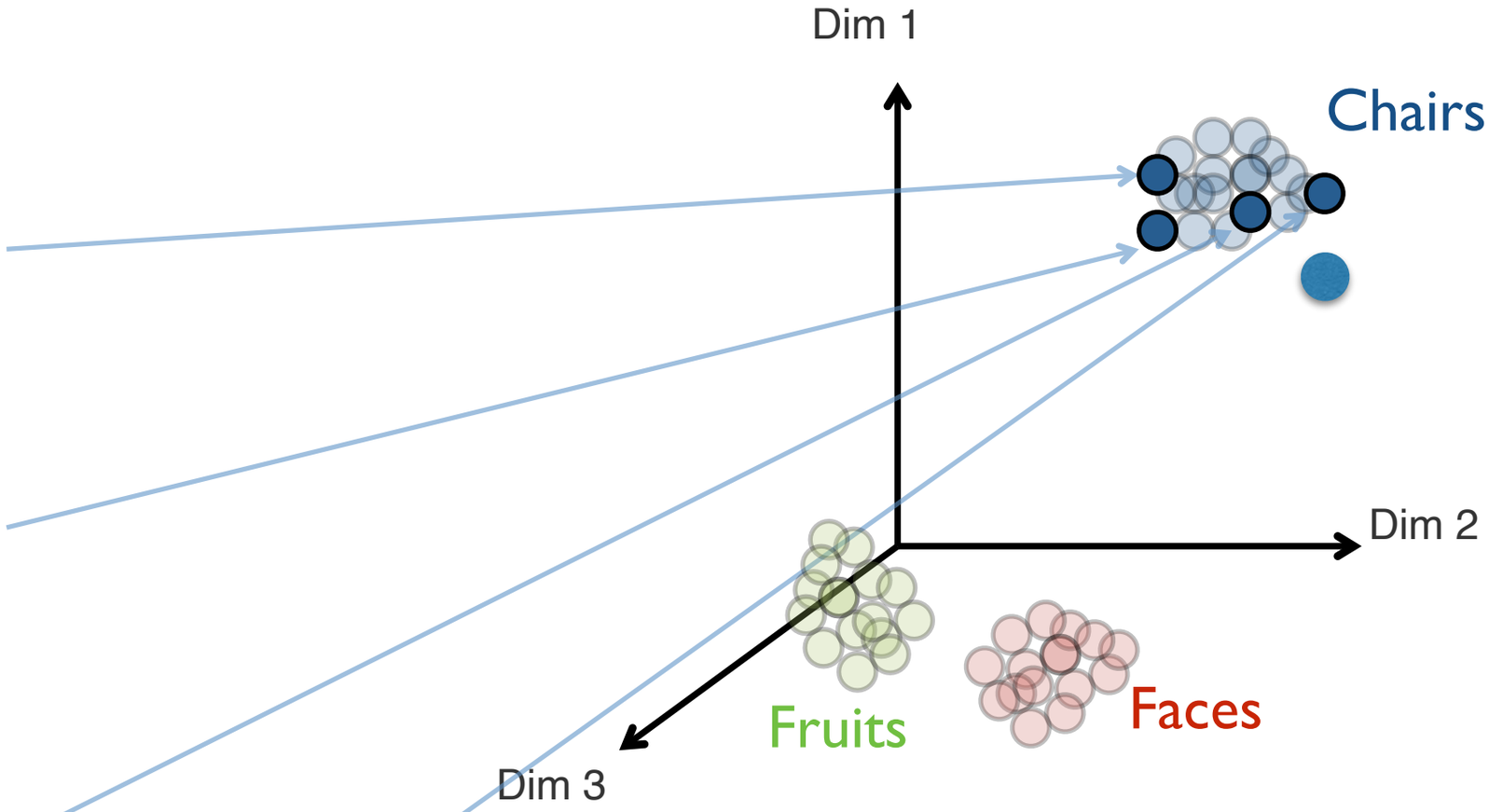
Idea of minimum distance classifiers:

For any new example, pick class whose mean is closest in feature space.

Minimum Distance Classifiers

Pixel space: $R^{\sim 1000000}$

IT feature space: $R^{4000(?)}$



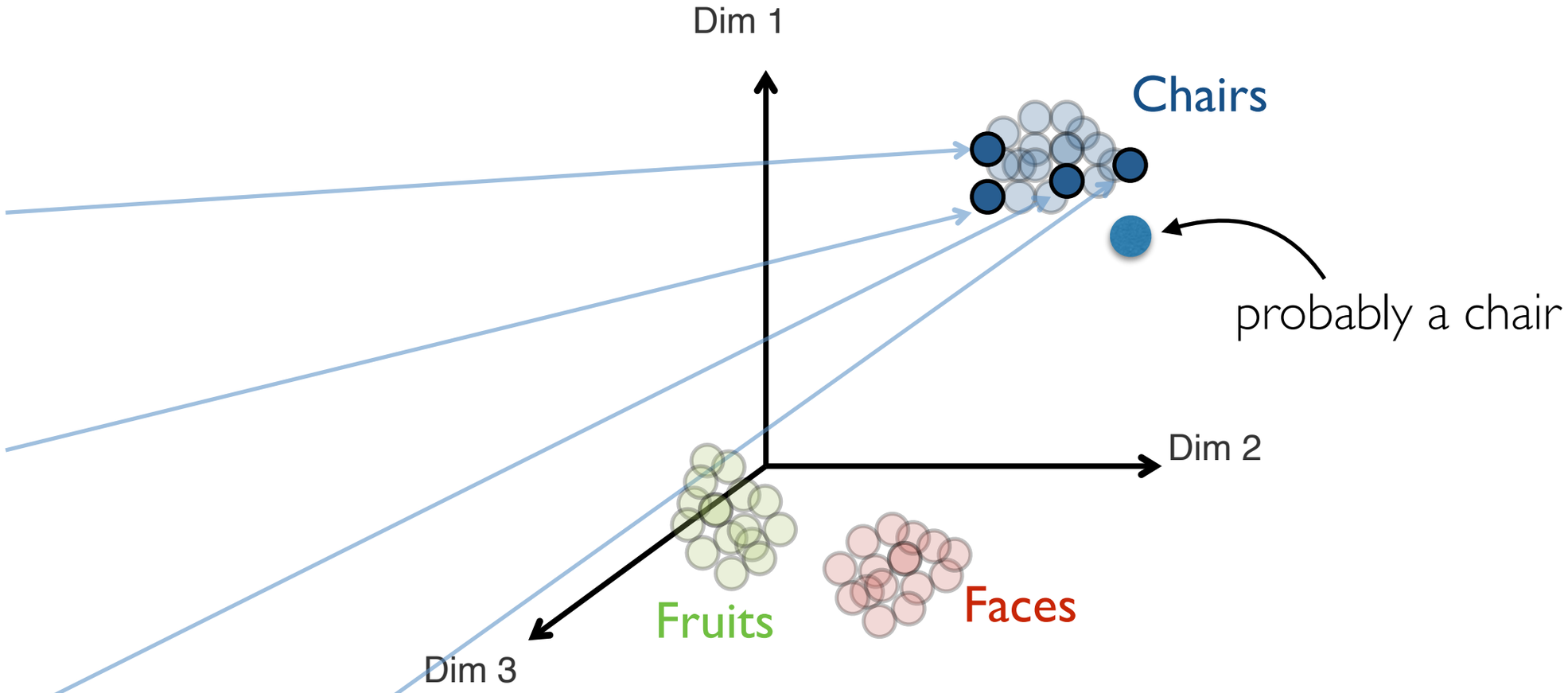
Idea of minimum distance classifiers:

For any new example, pick class whose mean is closest in neural space.

Minimum Distance Classifiers

Pixel space: $R^{\sim 1000000}$

IT feature space: $R^{4000(?)}$



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Minimum Distance Classifiers

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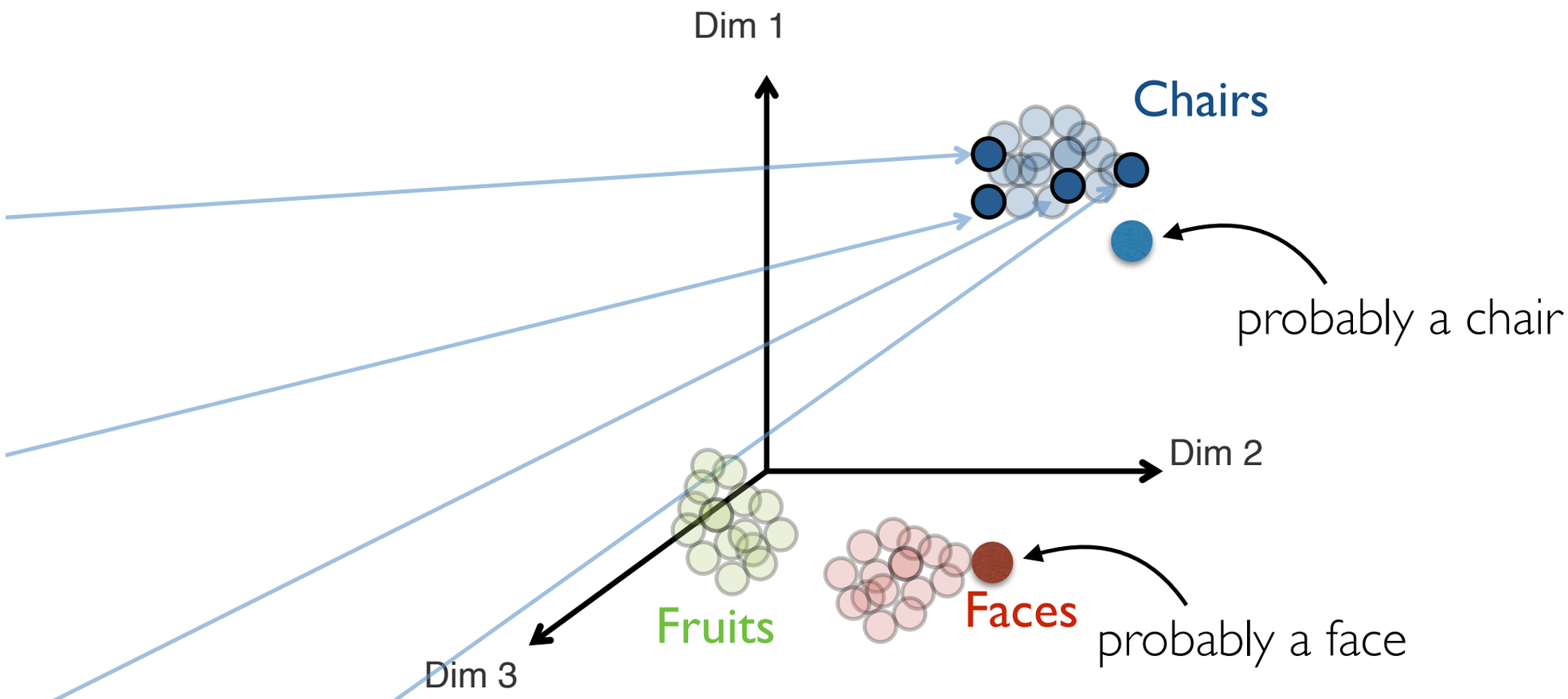


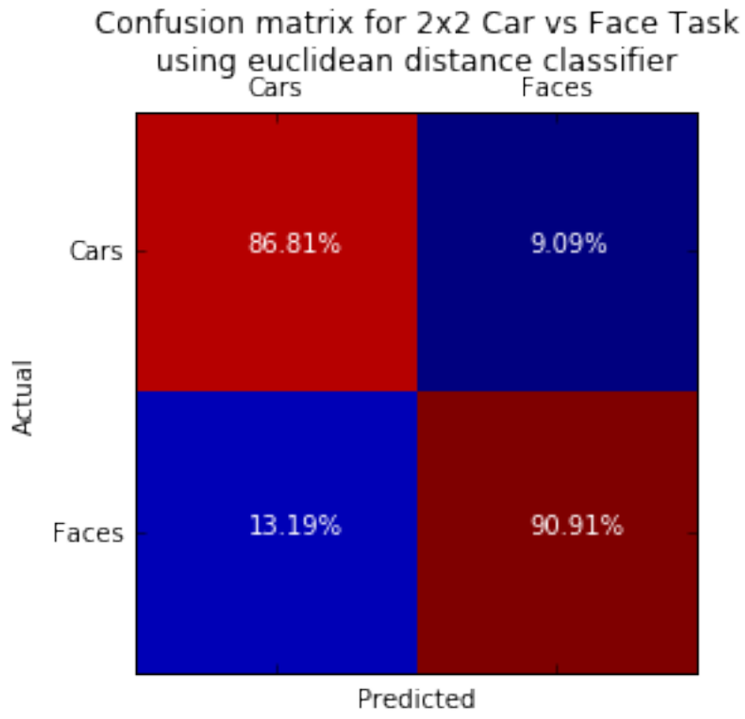
Idea of minimum distance classifiers:

For any new example, pick class whose mean is closest in neural space.

Minimum Distance Classifiers

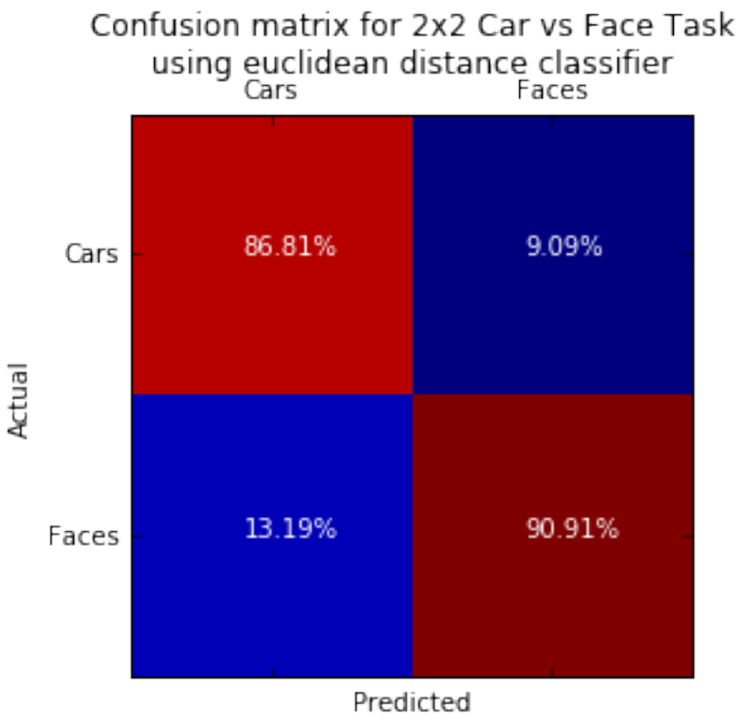
[IPYNB: Minimum Distance Classifiers]

Minimum Distance Classifiers



Simple correlations of neurons to stimulus properties

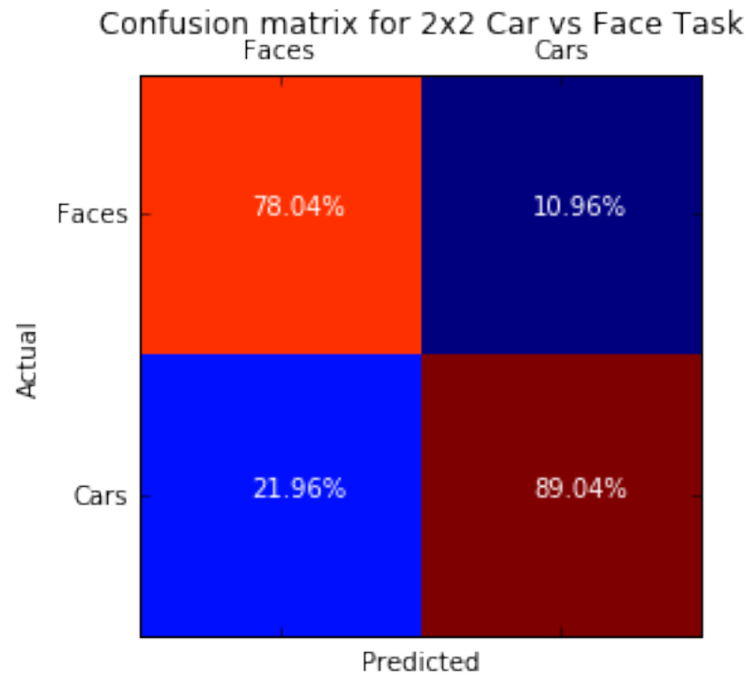
Face-vs-car
Minimum-distance classifier



Accuracy = 88.75%

Chance = 50%

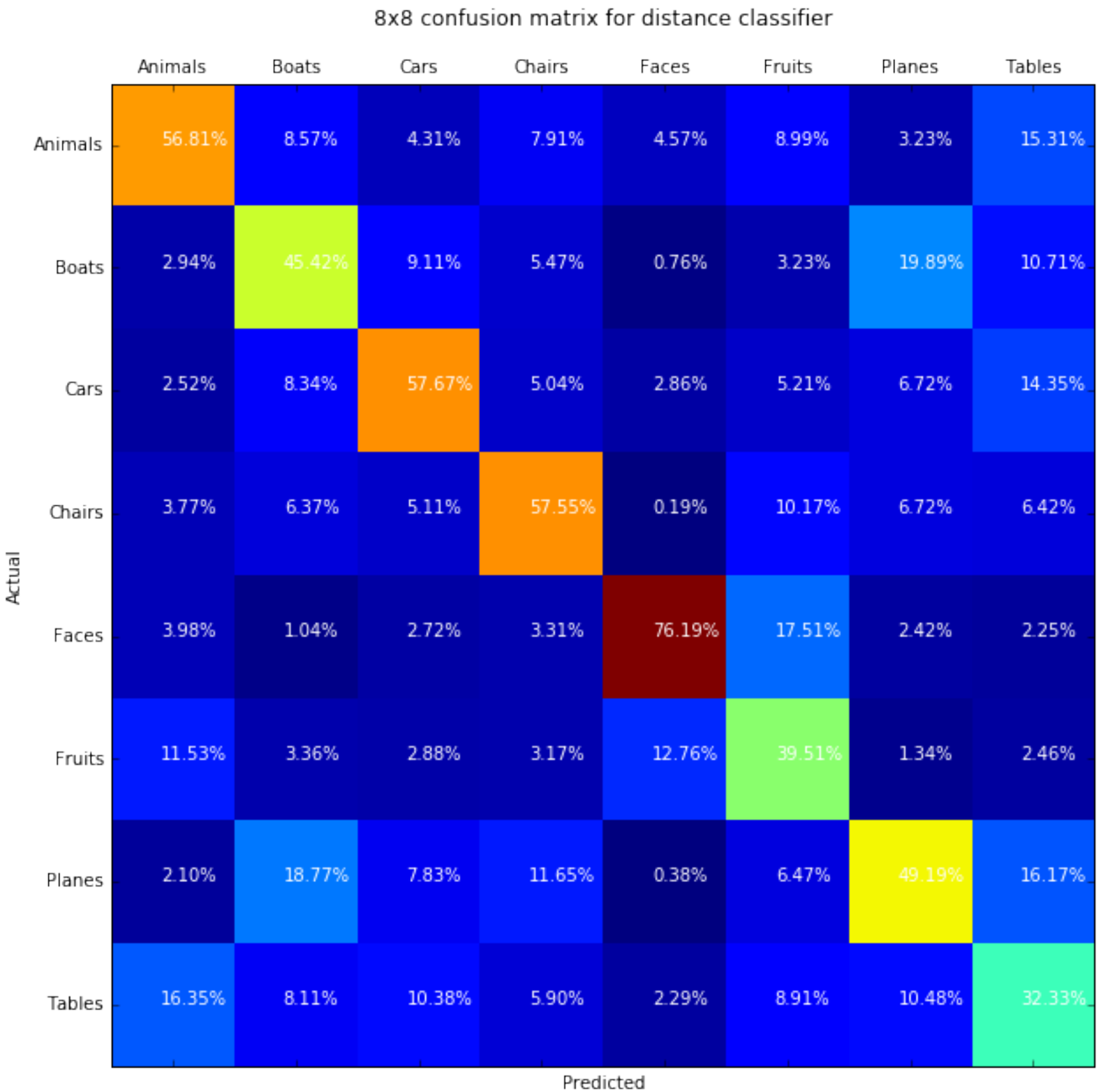
Face-vs-car
Single-best feature



Accuracy = 82.6%

Chance = 50%

Simple correlations of neurons to stimulus properties



Accuracy = 48.8%

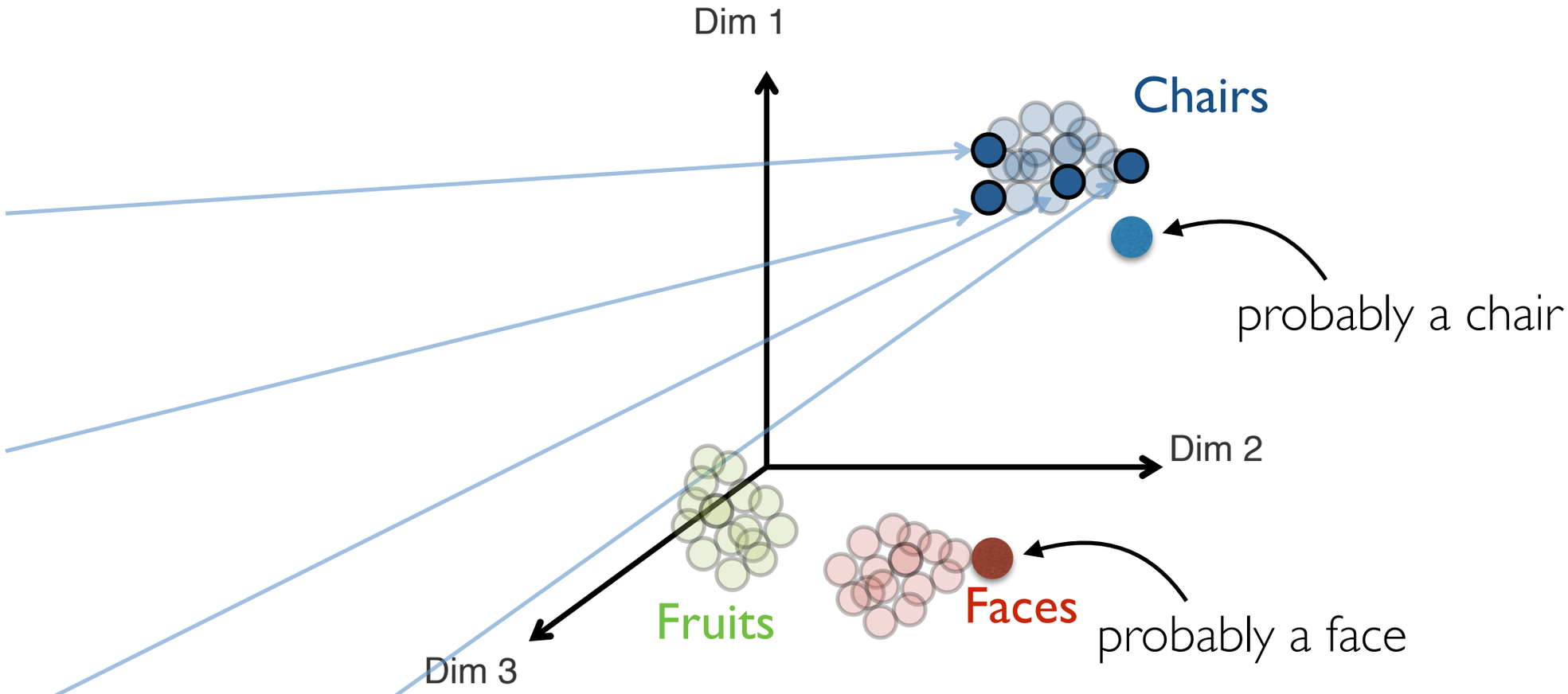
Chance = 12.5%

mean d-prime = 1.5

Neural Data as Feature Representations

Pixel space: $R^{\sim 1000000}$

IT feature space: $R^{4000(?)}$



Idea of minimum distance classifiers:

For any new example, pick class whose mean is closest in feature space.

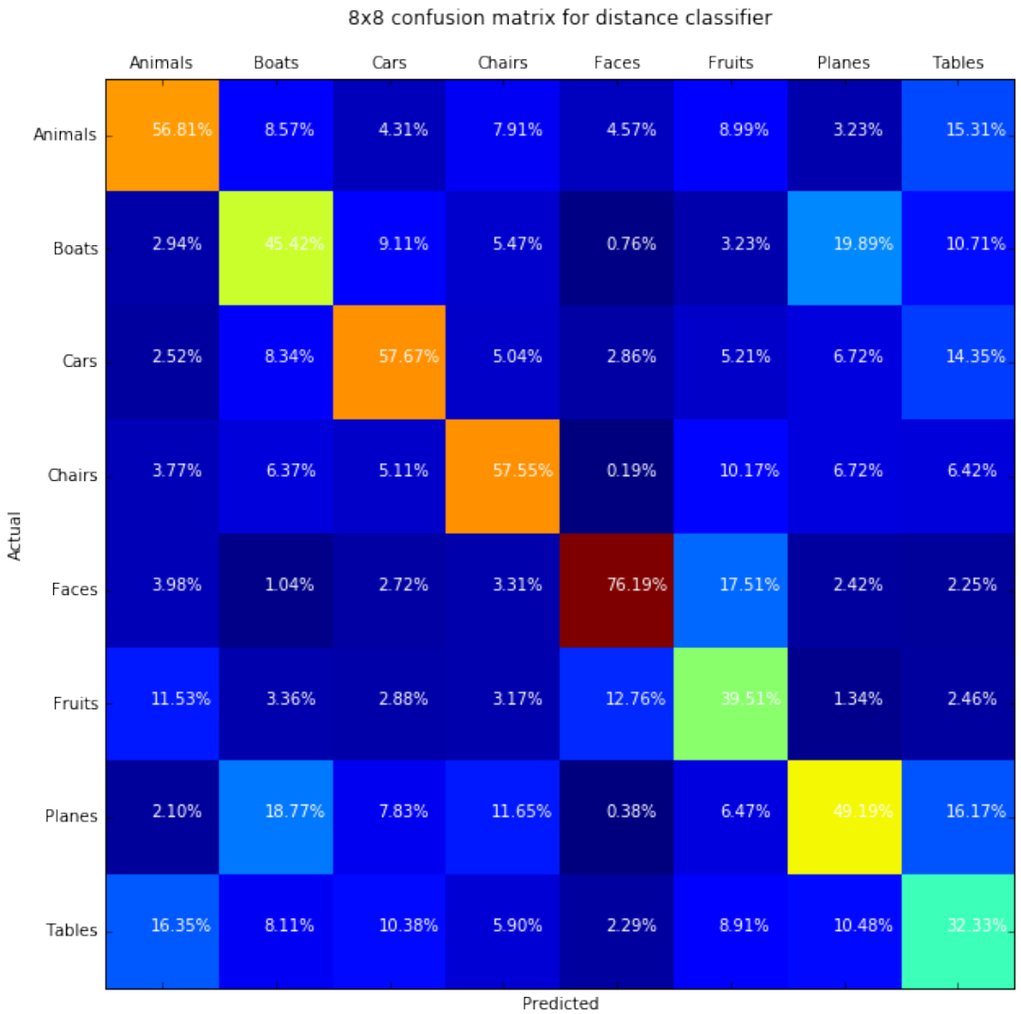
What if we used correlation distance rather than euclidean?

Minimum Distance Classifiers

[IPYNB: Maximum Correlation Classifiers]

Minimum Distance Classifiers

8-way min. Euclidean distance

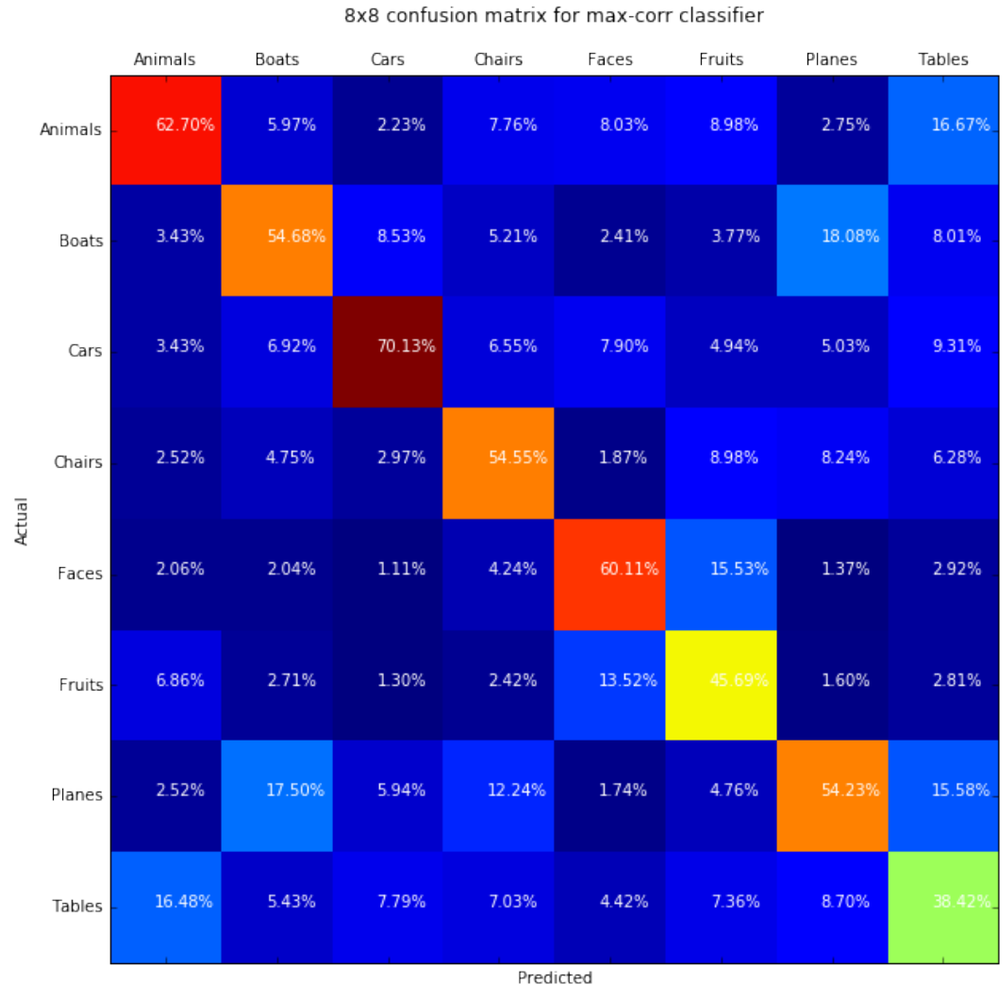


Accuracy = 48.8%

Chance = 12.5%

mean d-prime = 1.5

8-way max-correlation



Accuracy = 53.0%

Chance = 12.5%

mean d-prime = 1.6

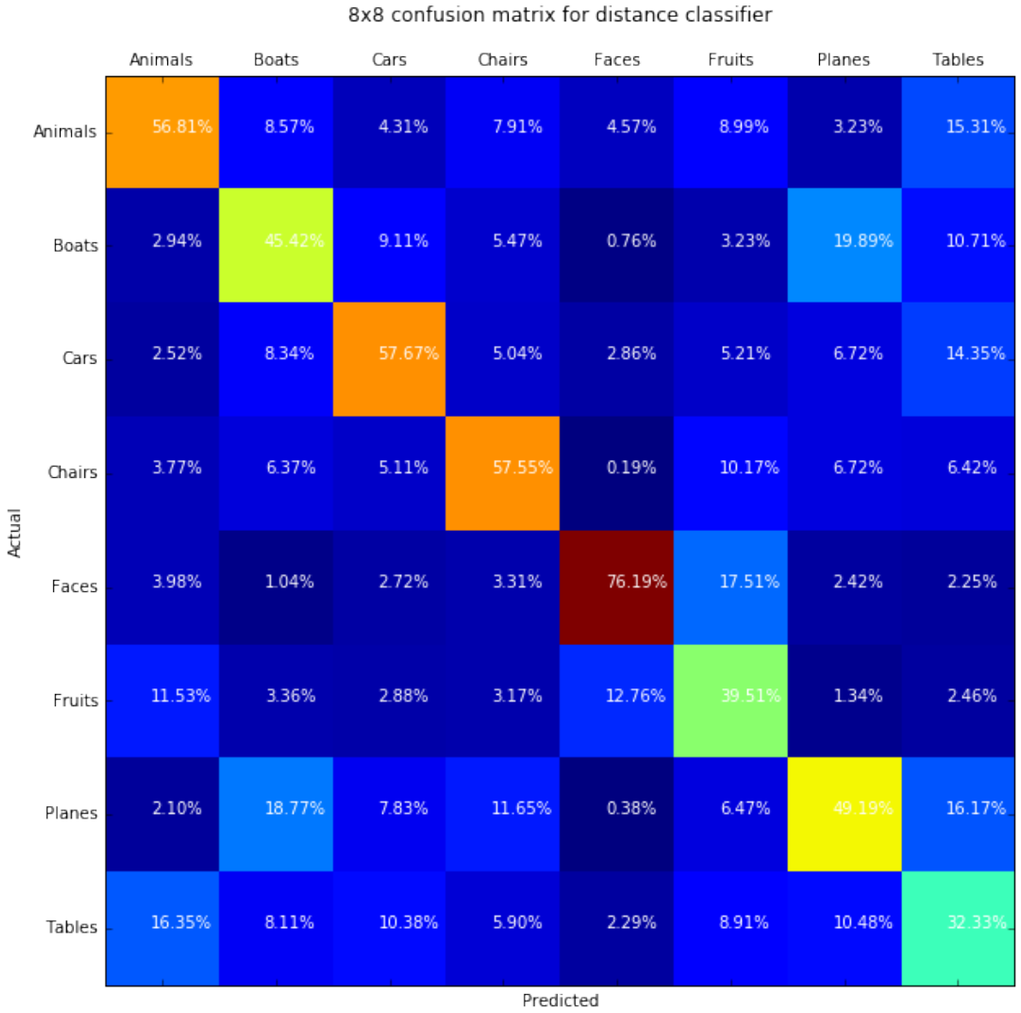
Minimum Distance Classifiers

Correlation Classifier seems a little better than the euclidean distance classifier

Norming the data helps a little as well.

Minimum Distance Classifiers

8-way min. Euclidean distance

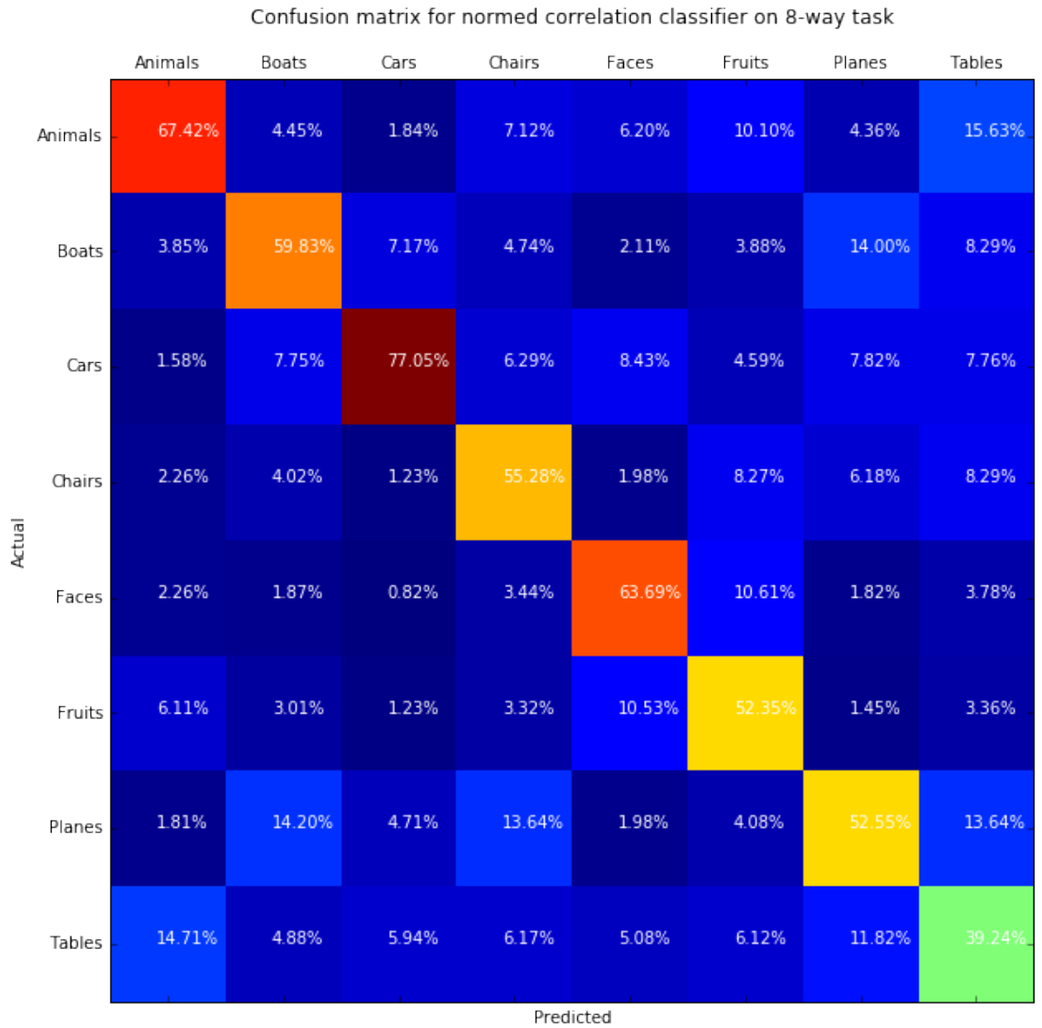


Accuracy = 48.8%

Chance = 12.5%

mean d-prime = 1.5

8-way max-correlation normed



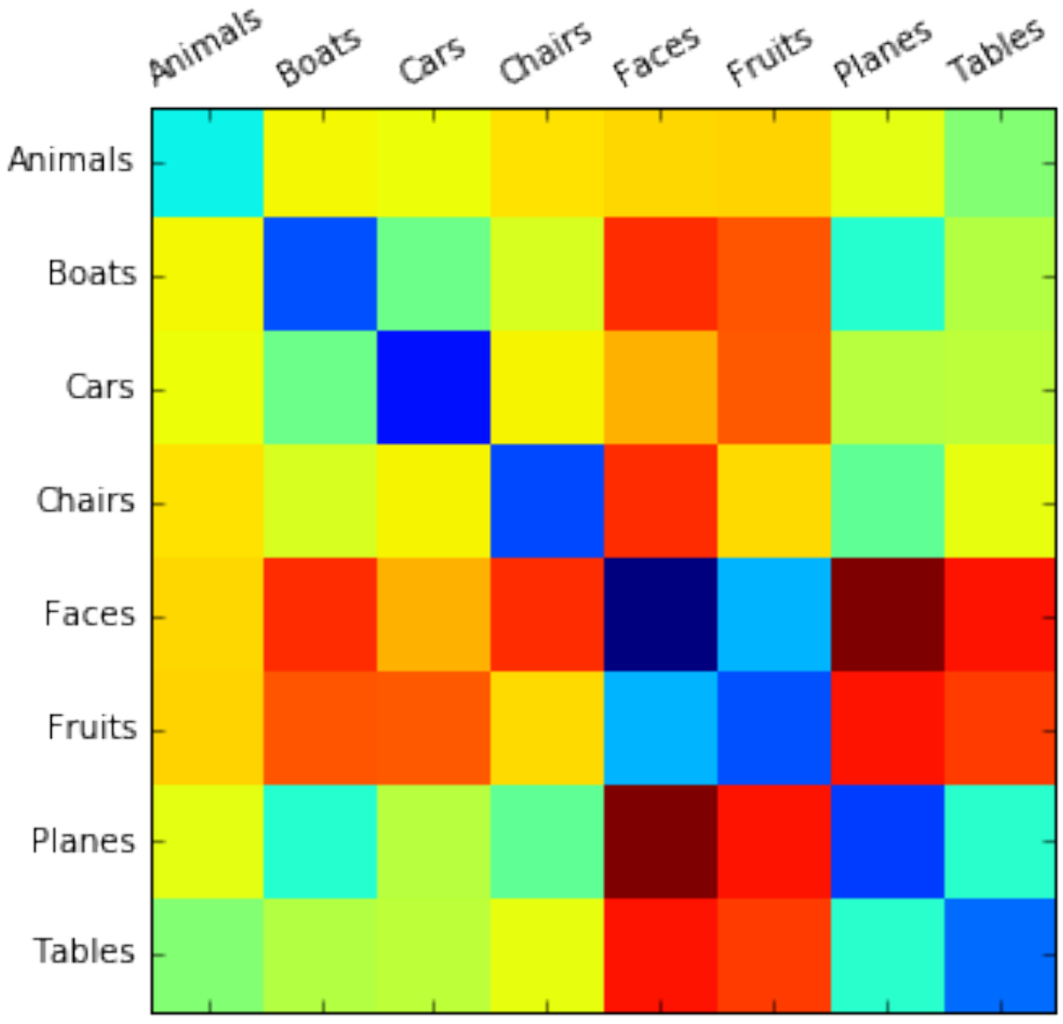
Accuracy = 56.3%

Chance = 12.5%

mean d-prime = 1.75

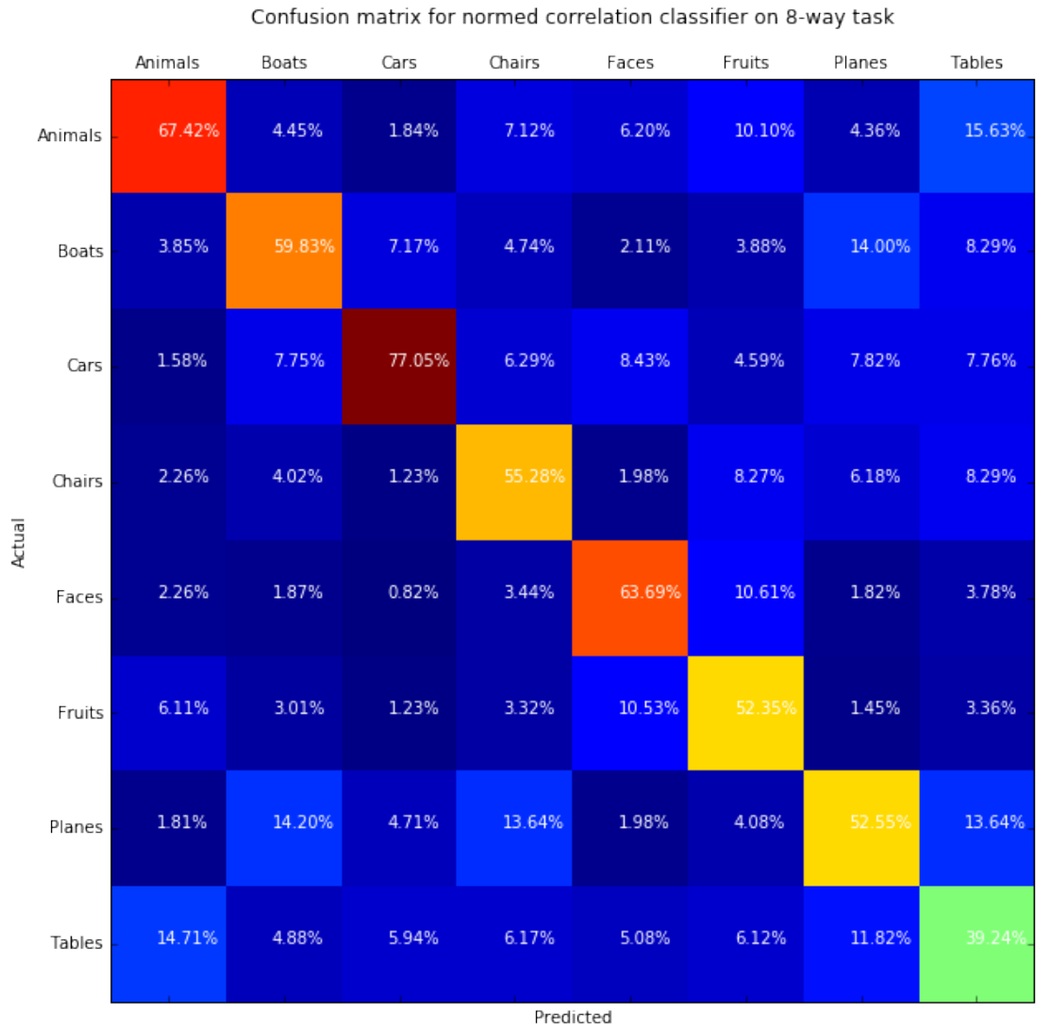
Minimum Distance Classifiers

Correlation matrix



No feature-specific weighting

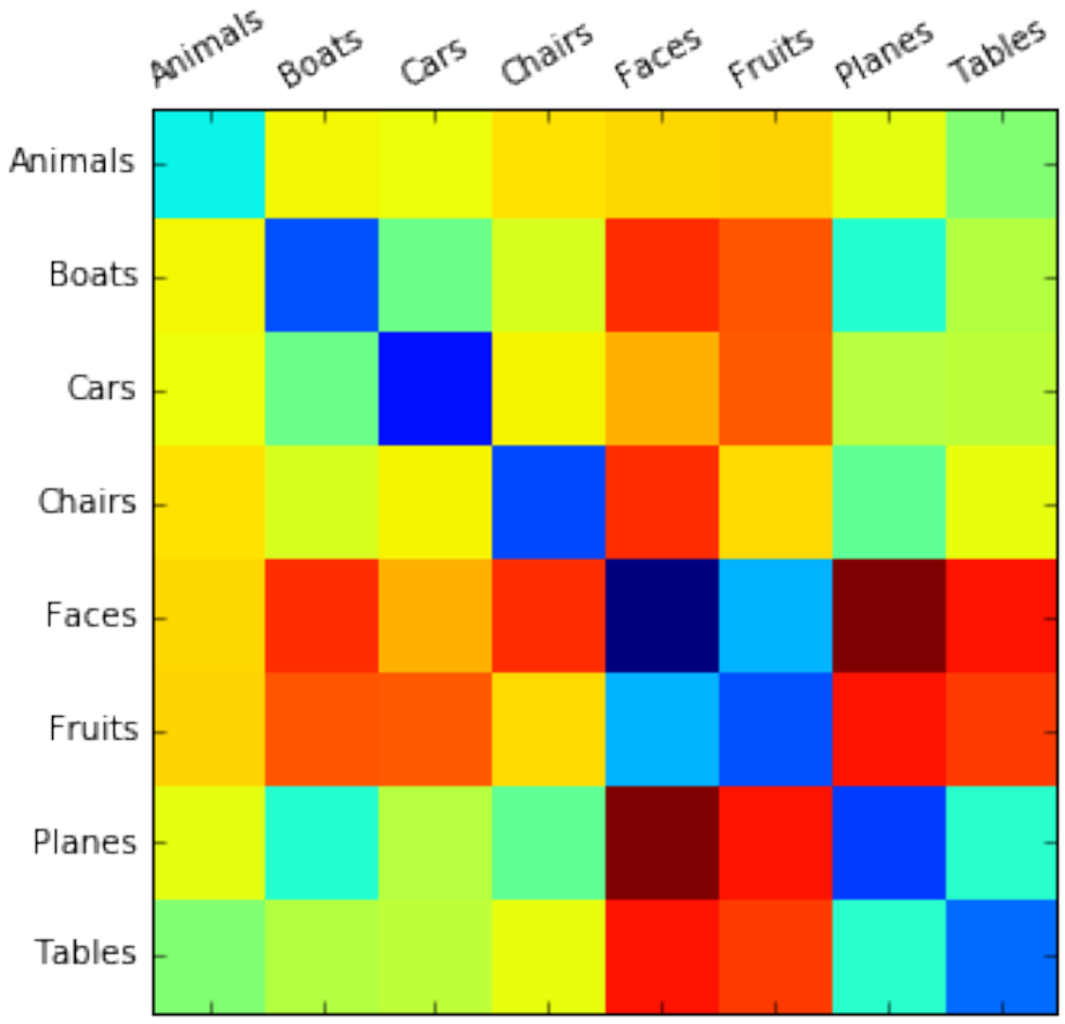
Confusion matrix



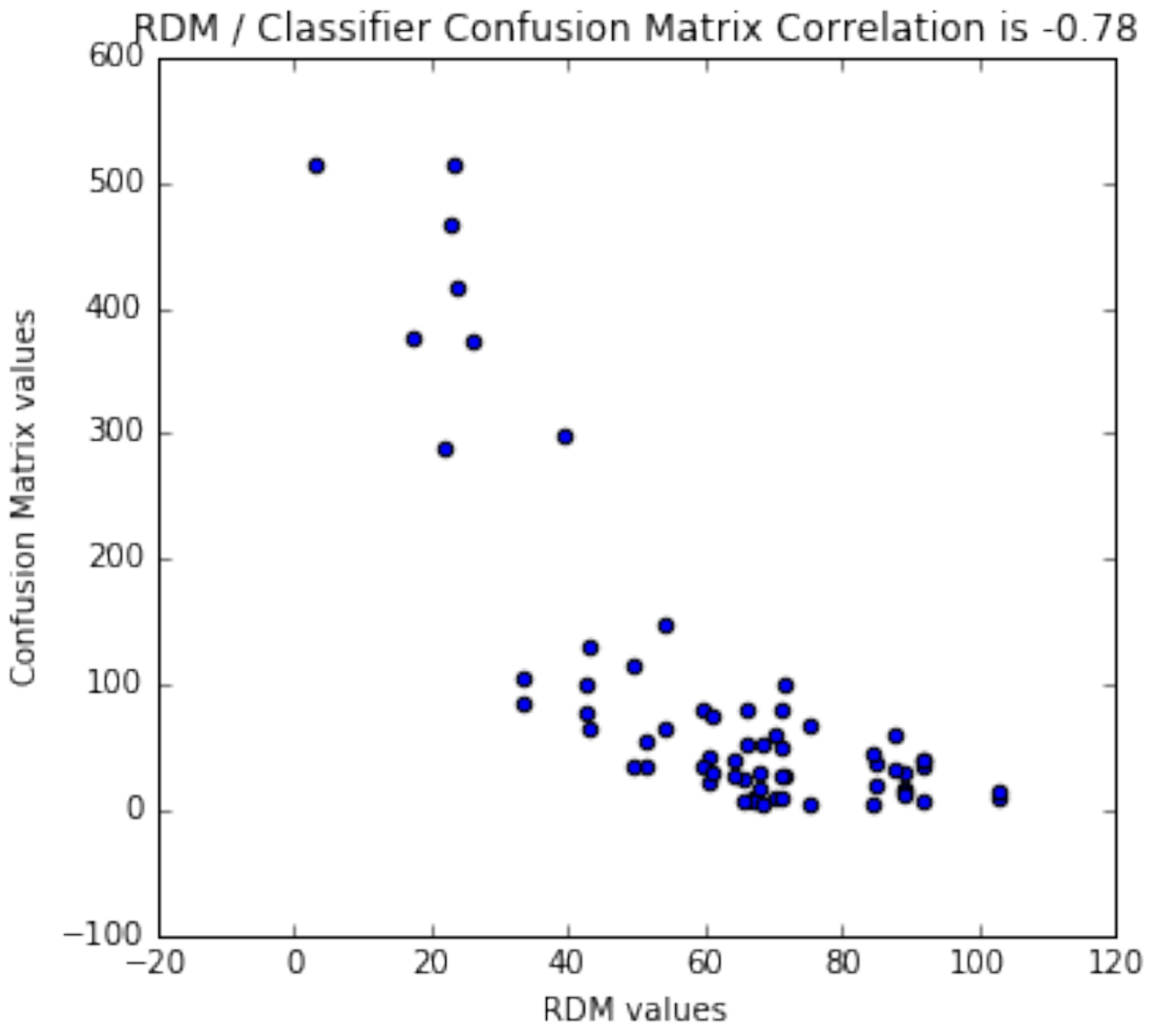
Uses correlation-based weighting

Minimum Distance Classifiers

Correlation matrix



Confusion matrix vs correlation matrix

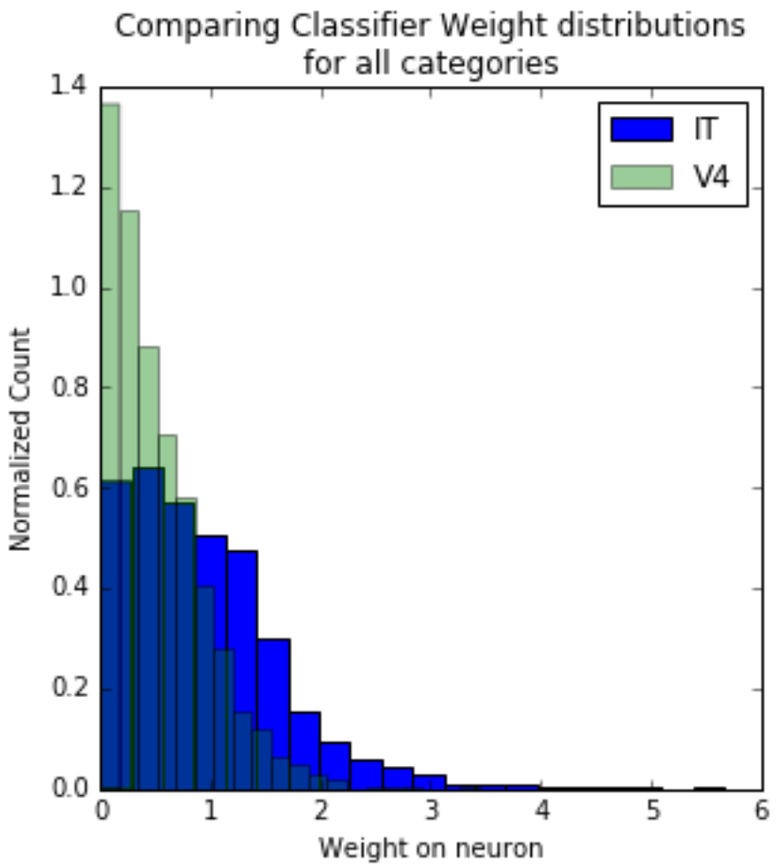


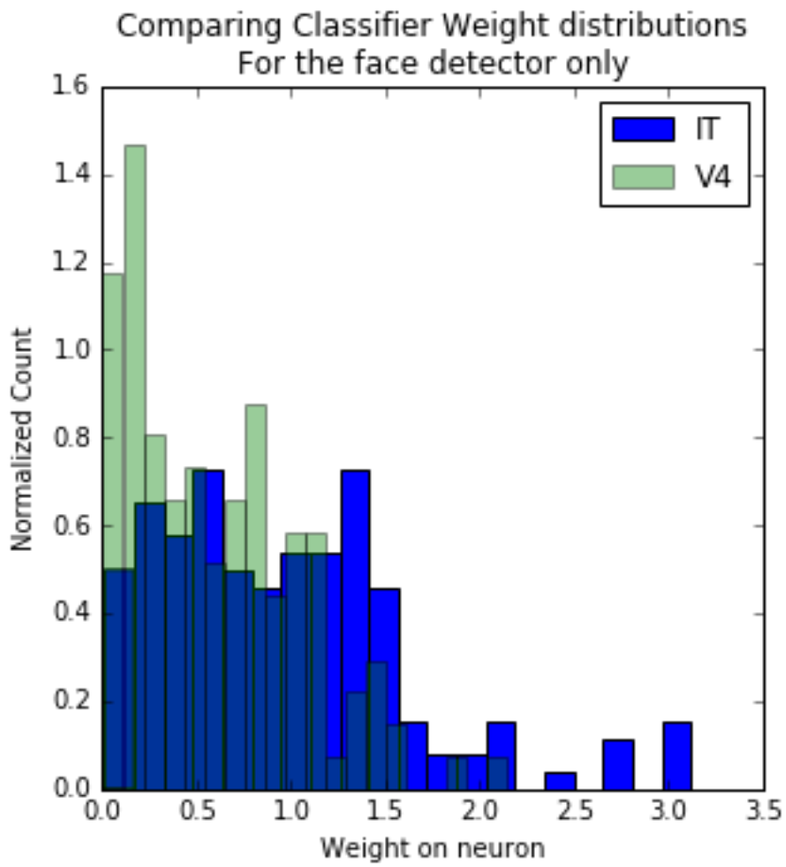
Minimum Distance Classifiers

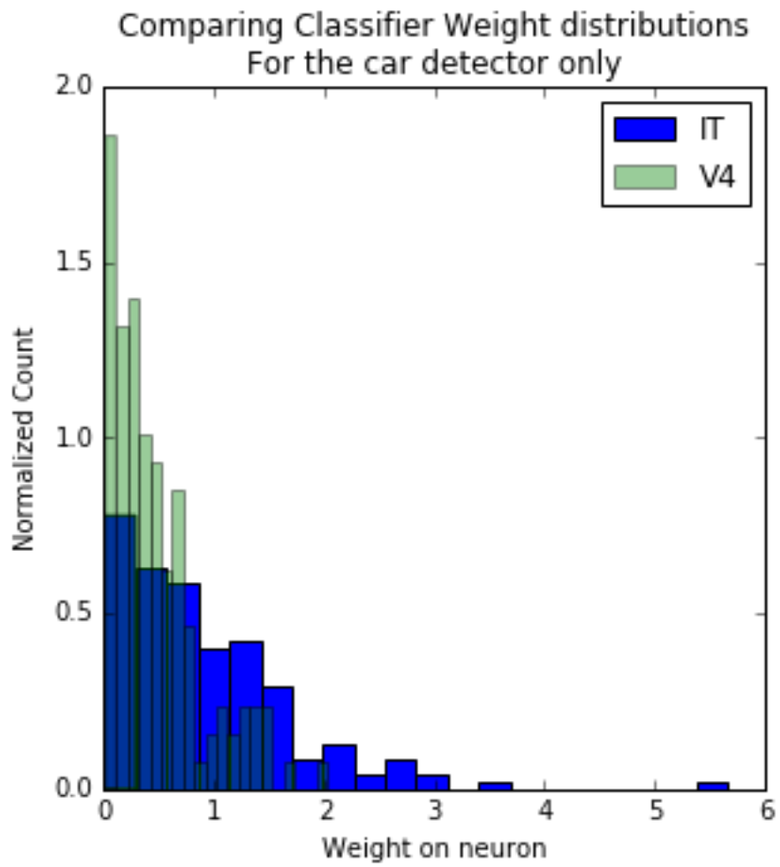
[IPYNB: Comparison of V4 and IT]

Minimum Distance Classifiers

IT neurons are doing most of the work in our classifiers.







Cross Validation

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key thing in all cases: training/test CANNOT overlap!

Cross Validation

[IPYNB: Getting Splits for Cross-Validation]

Cross Validation

```
Procedure:

    splits = get_splits(split arguments)

    For each split:

      estimate model params on training data

      evaluate performance on testing data

average results over splits
```

Object-Oriented Programming (OOP)

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bazz = Baz(1, 2)      bazz.bar(10) ??
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bazz = Baz(1, 2)

bazz.bar(10) = self.foo(10) * self.b
             = (10**2)/self.a * self.b = 200
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  def predict(self, test_data):
    returns actual discrete predictions
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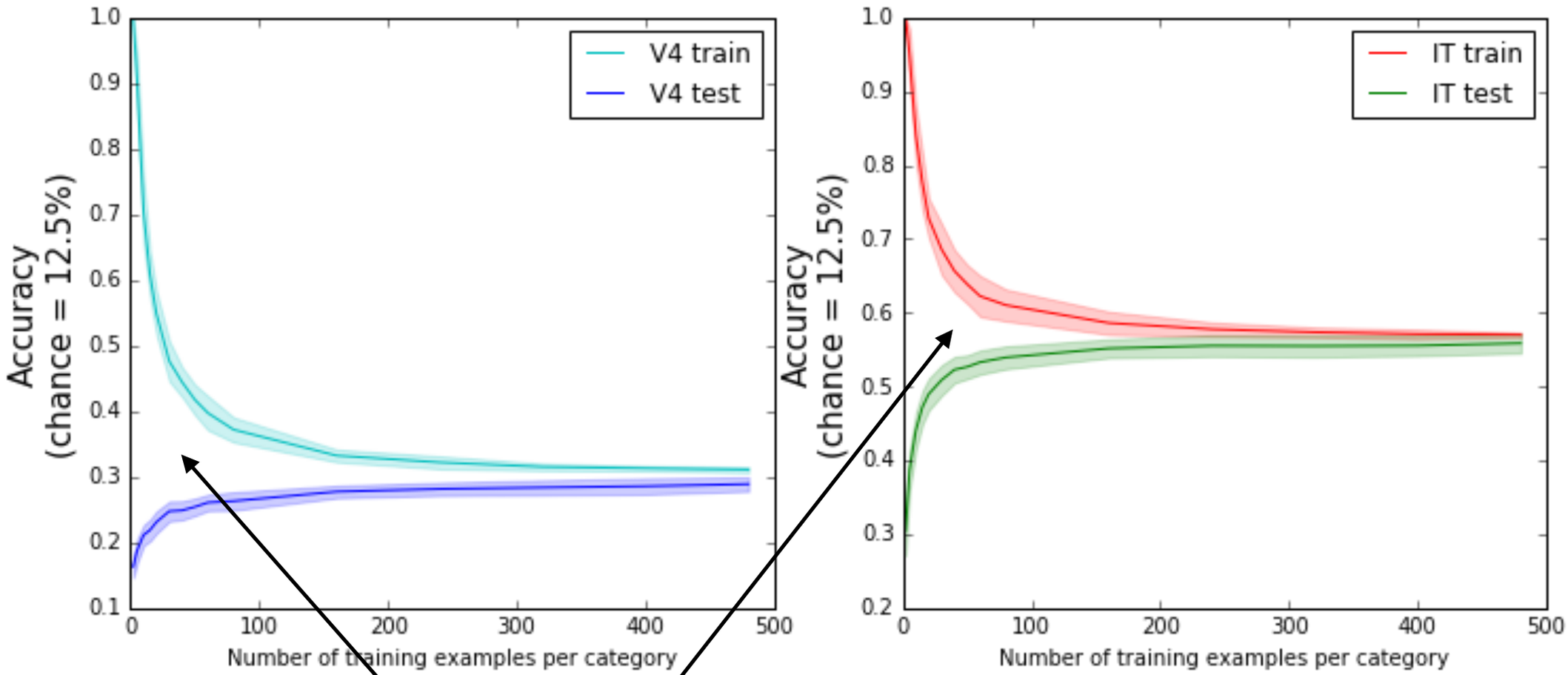
creates a new model instance for each split

Cross Validation

[IPYNB: The Train-Test Procedure]

Cross Validation



OVERFITTING