Disparity-Based Collision Avoidance System

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Deep Learning Project
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1 Introduction

The goal of our project is to predict the distance to the nearest object on the road from a single image. Neural Networks are widely used in Advanced Driver Assistance Systems (ADAS) and this problem has direct application in Camera-Based Forward Collision Alert System.

Ordinary, disparity map is built based on stereo pair and then camera parameters are neccessary for depth map building.

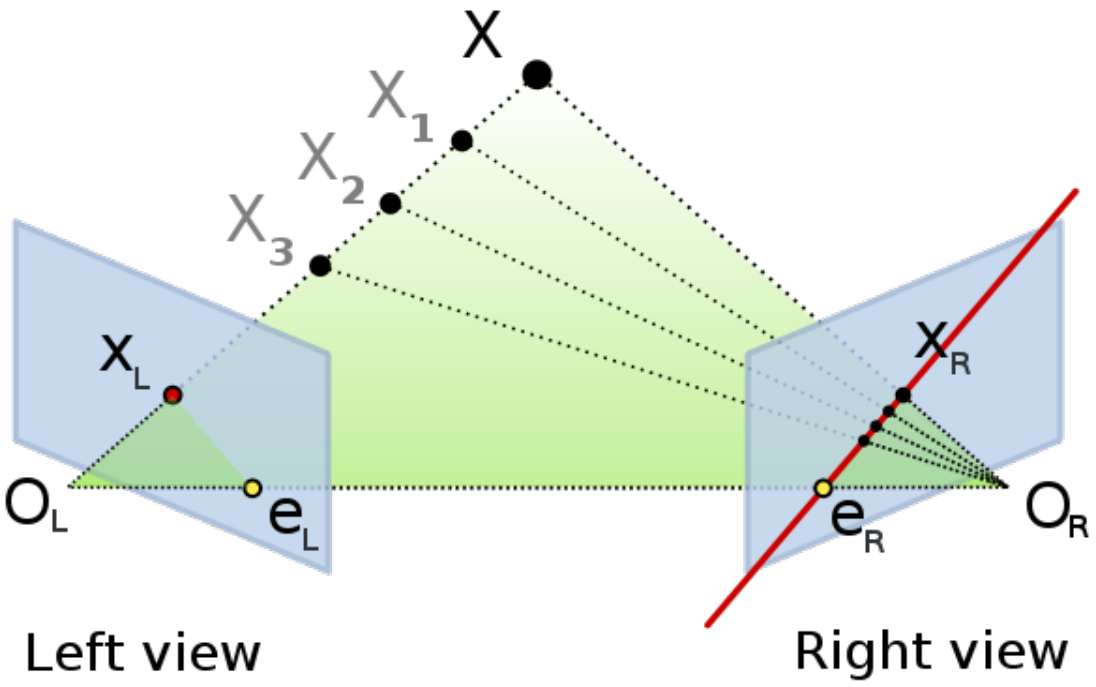


Figure 1:

We use semantic annotated data CityScapes and all intristic parameters are known, so the goal was to predict the robust maximum for disparity map, corresponded o the closest object on the road.

As long as we are interested only in objects on the way of the car, we work not only with the entire image, but also with its Region of Interest (RoI).

2 Related work

There are several works related to the whole depth map prediction, based on Deep Learning. In *'Depth Map Prediction from a Single Image using a Multi-Scale Deep Network', 2015* authors consider two steps (coarse-scale and fine-scale) NN Structure. The task of the coarse-scale network is to predict the overall depth map structure using a global view of the scene. After taking a global perspective, local refinements are made by fine-scale network.

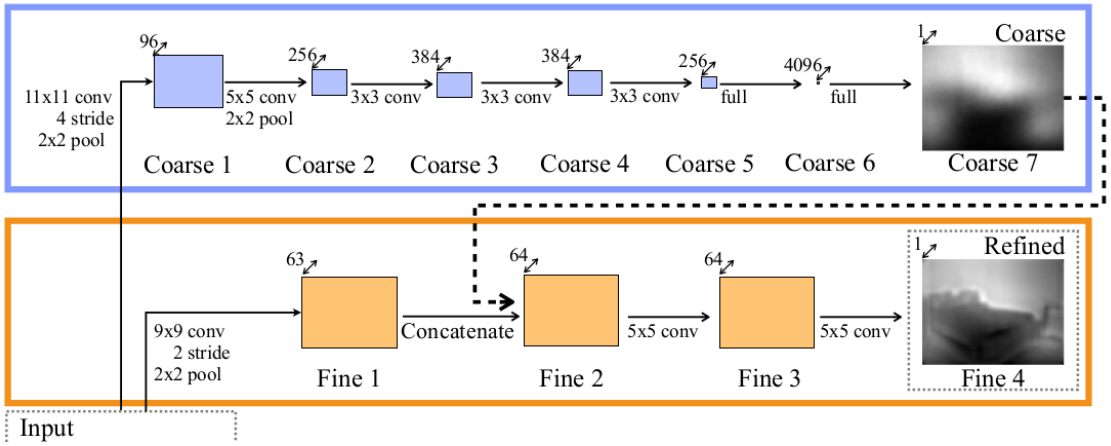


Figure 2:

The highly impressive result motivated us to use deep learning approaches for our task.

3 Problem setting

The mathematical formulation of problem we deal with is the following.

X — RGB pictures

Y — labels

$X^n = \{(x_1, y_1), \ldots, (x_n, y_n)\}$ — training set, where y_i is the maximum disparity for the picture x_i.

Find the algorithm $a : X \to Y$, which generalizes the target function.

If we replace y_i with the label of bin where y_i occurs we will get formulation of classification problem.

Classification statement has several advantages over regression:

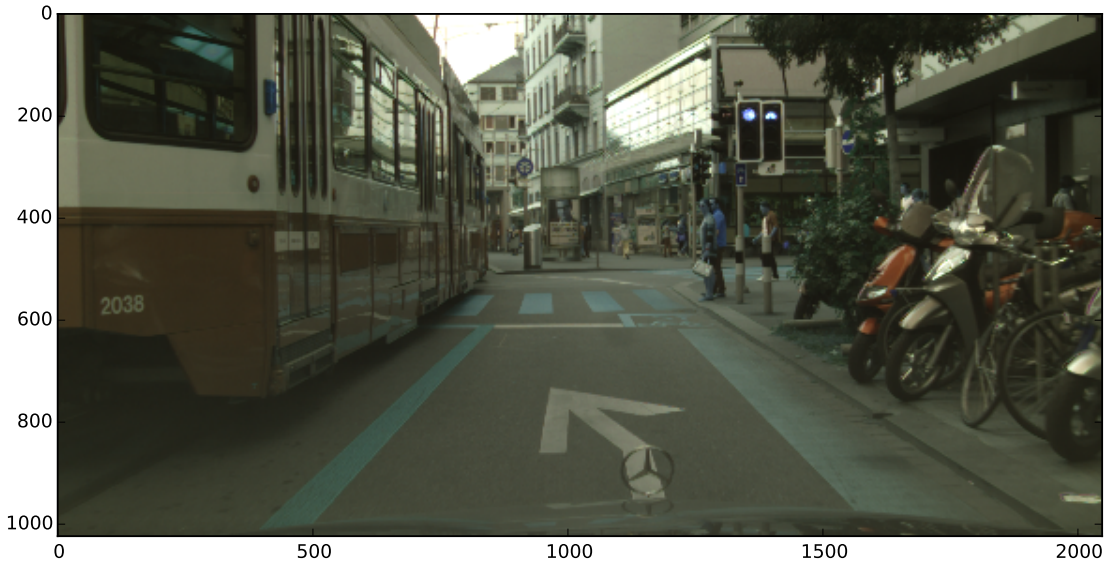
- Classification is easy to train than regression,
- We can easily predict probability for each class (far, close, very far, very close, etc.).

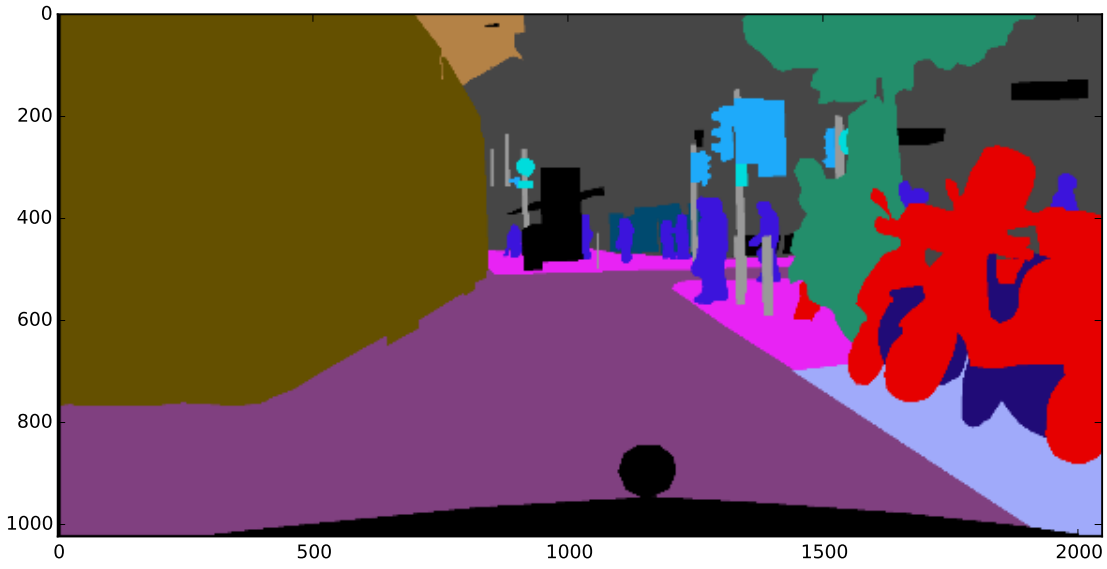
So, further we consider the problem with 2 or 4 classes.

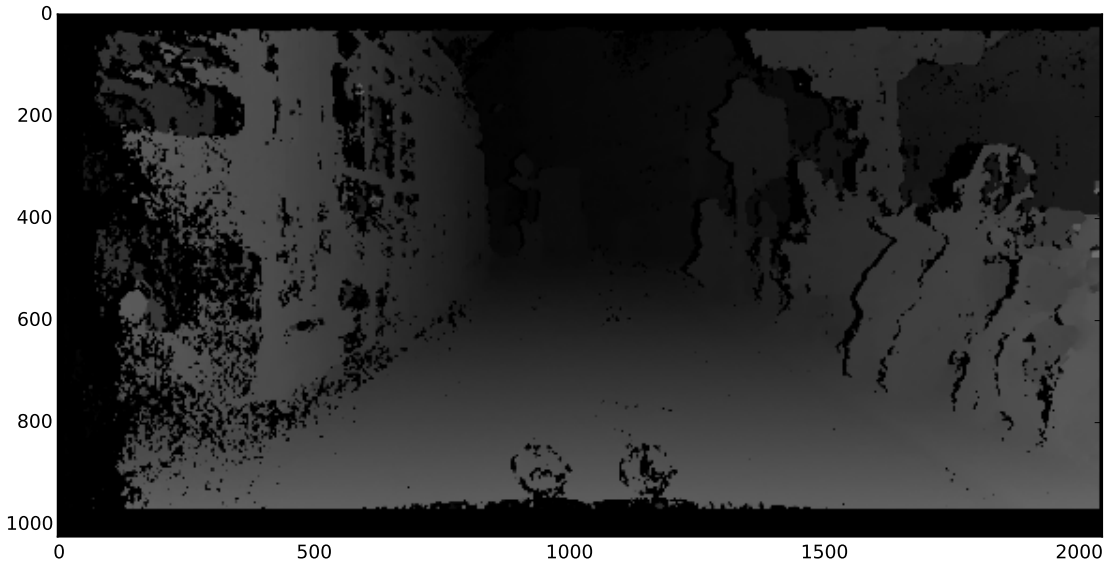
4 Training set preparation

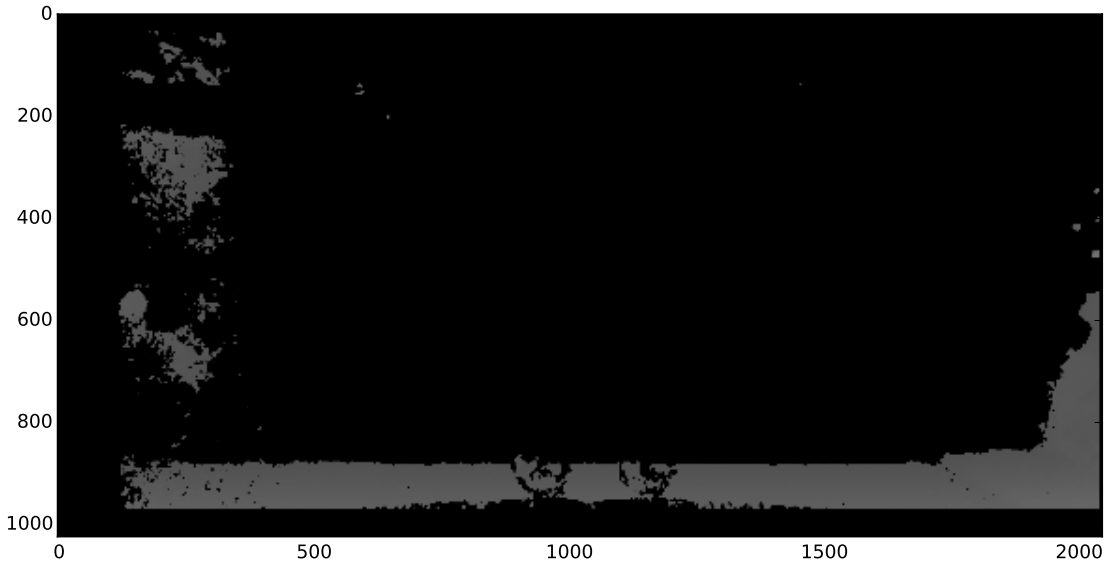
Typical cityscapes data looks as follows.

In [8]:
```
# good example nmb_image = 41, 12
i = np.random.randint(0, len(disp_imgs_paths))

disp = cv2.imread(disp_imgs_paths[i])
img = cv2.imread(imgs_paths[i])
img_path = imgs_paths[i]
anno_img = cv2.imread(anno_imgs_paths[i])

Plot(img)
Plot(anno_img)

''' All disparity'''
Plot(disp)

''' Disparity in percentile '''
disp_perc = disp.copy()
disp_perc[disp < np.percentile(disp, 90)] = 0
Plot(disp_perc)
```



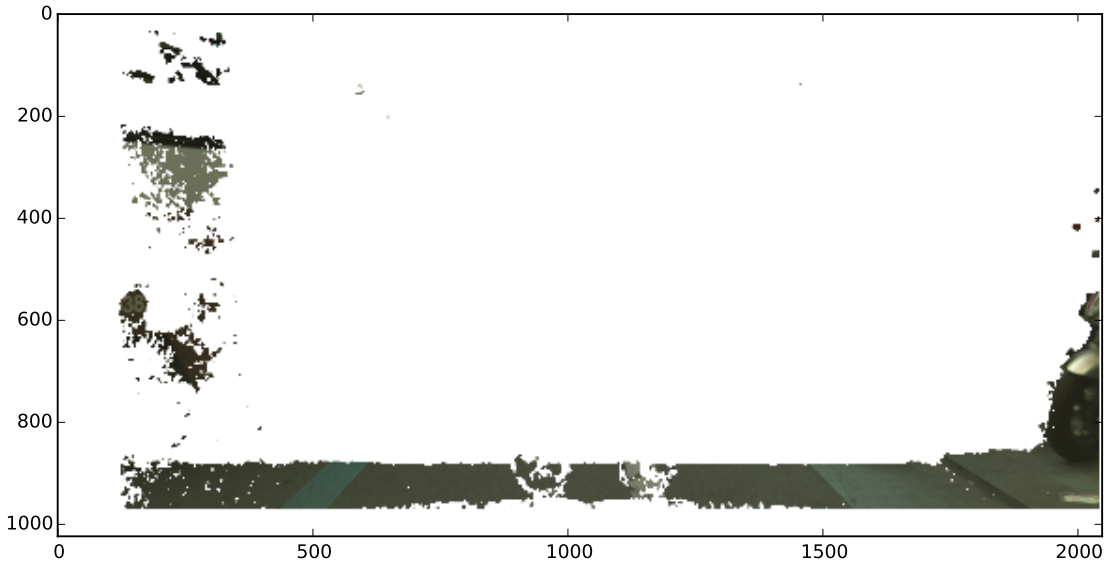

0
200
400
600
800
1000
0
500
1000
1500
2000


0
200
400
600
800
1000
0
500
1000
1500
2000



One can see that maximum disparity or any its percentile is meaningless for training set construction and physically trivial.

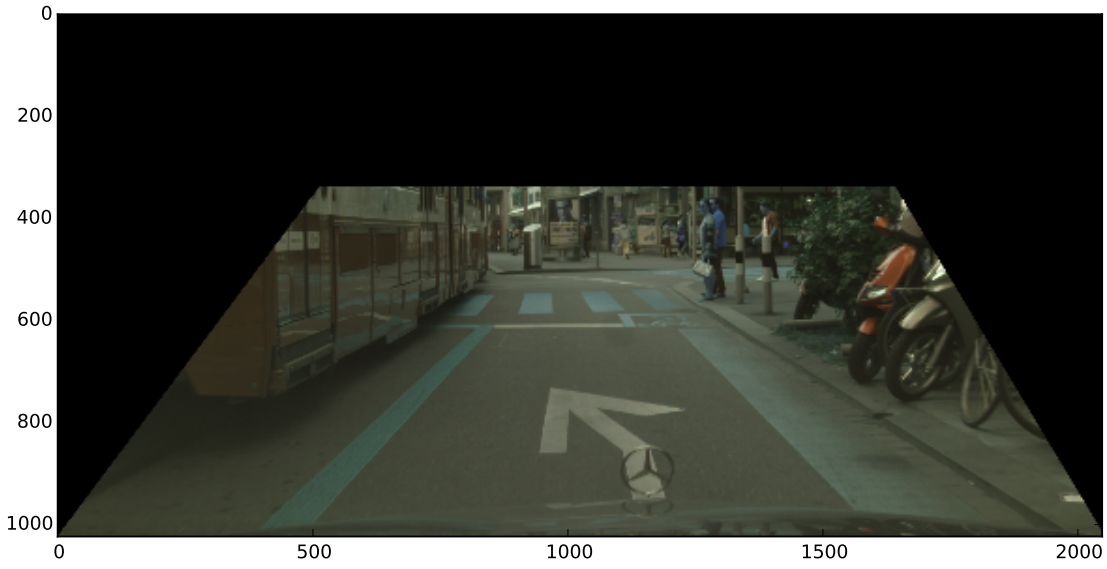
```
In [10]: img_perc = img.copy()
         img_perc[disp < np.percentile(disp, 90)] = 255
         Plot(img_perc)
```



So, first, the road obviously has to be removed and second, we extract target labels just for region of interest.

4.1 RoI selection

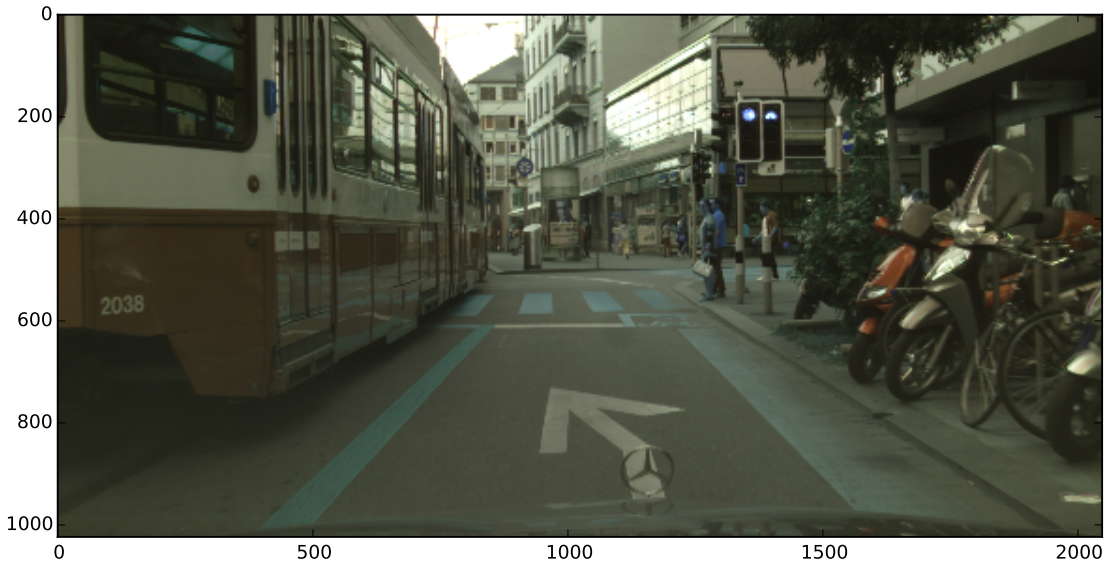
```
In [11]: Plot(CropRoI(cv2.imread(img_path, -1)))
```

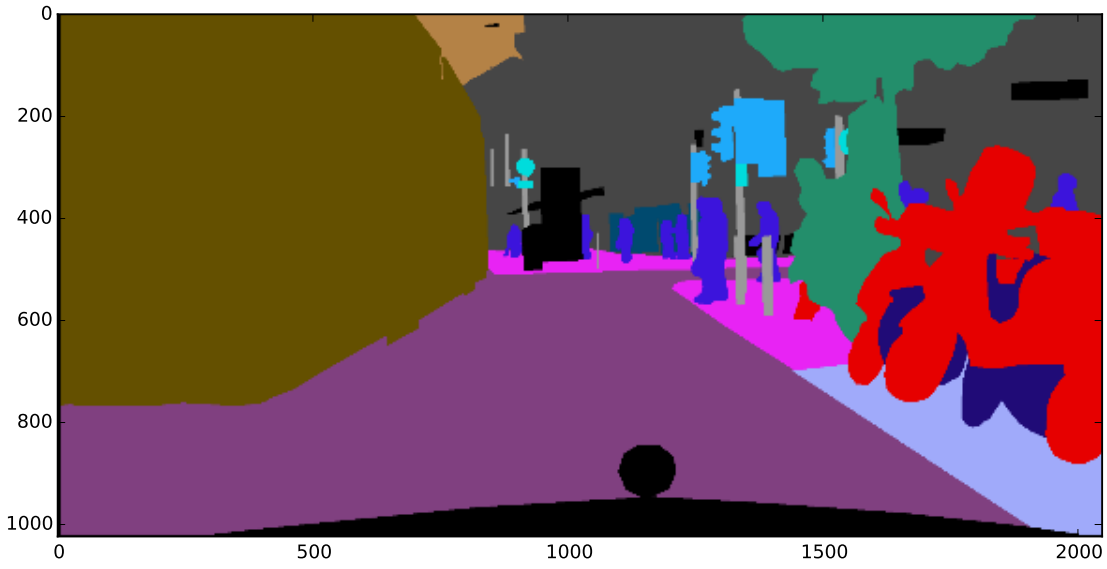


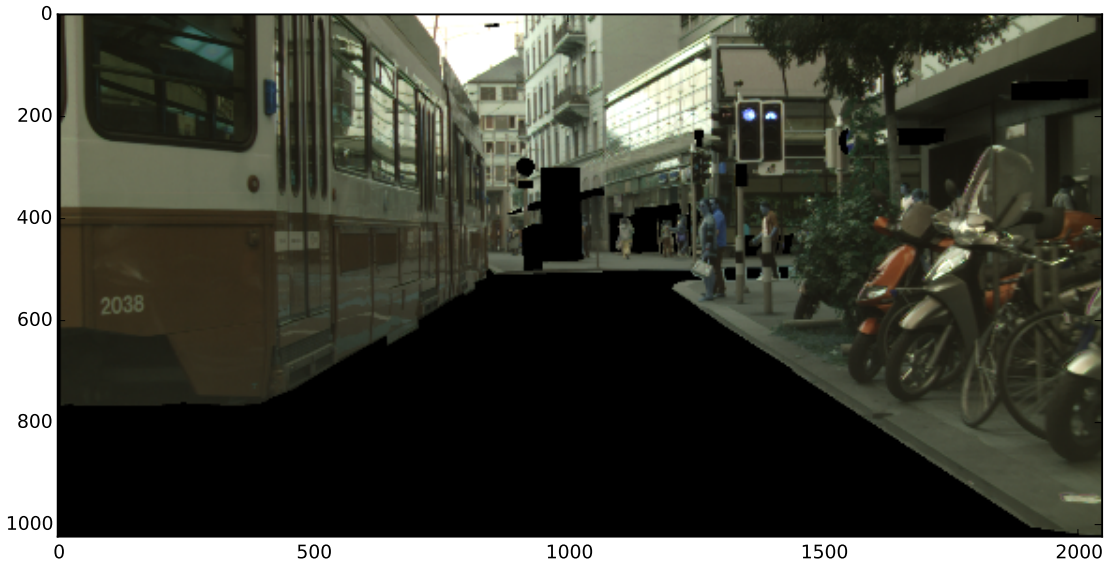
4.2 Exluding Road

We remove the road and car logo with the hood from the picture using fine segmentation provided by cityscapes team.

```
In [12]: Plot(img)
         Plot(anno_img)
         masked_img = ExcludeRoadDisp(img, anno_img, [(128, 64, 128), (0, 0, 0)])
         Plot(masked_img)
```



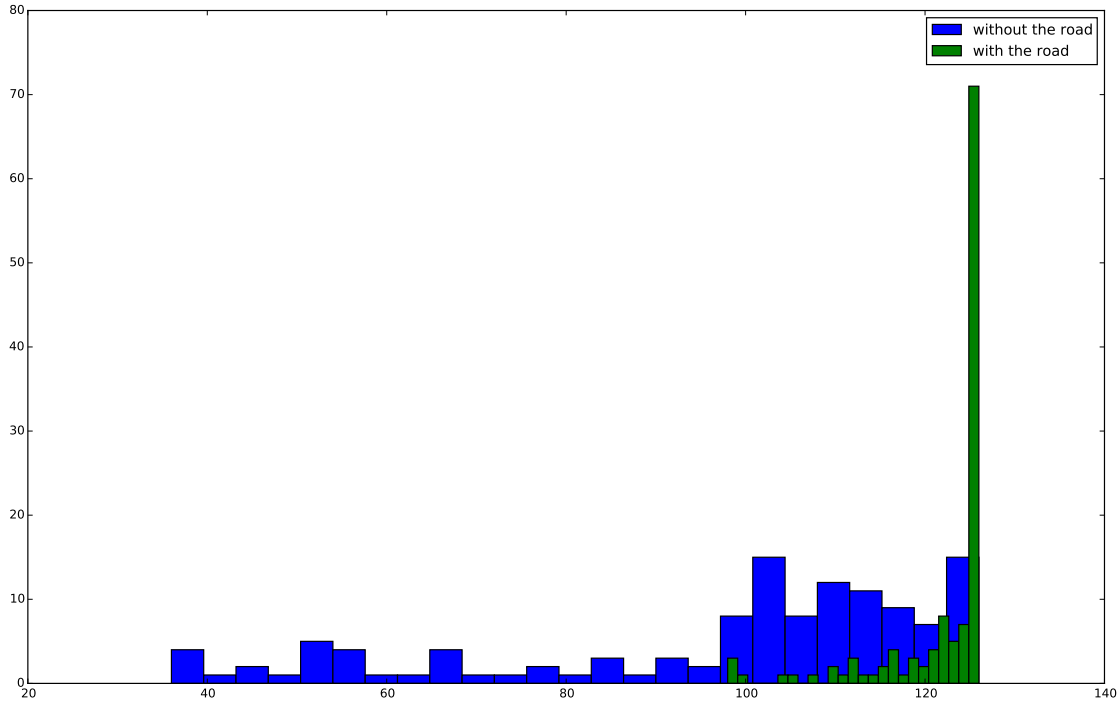




As a result, we got disparity distribution that makes sence and let the problem setting physically meaningful.

```
In [18]: plt.figure(figsize=(16, 10))
         plt.hist(max_disps_excl, bins=25, label='without the road')
         plt.hist(max_disps, bins=25, label='with the road')
         plt.legend(loc='best')
```

```
Out[18]: <matplotlib.legend.Legend at 0x4097fd0>
```



5 Features as CNN output

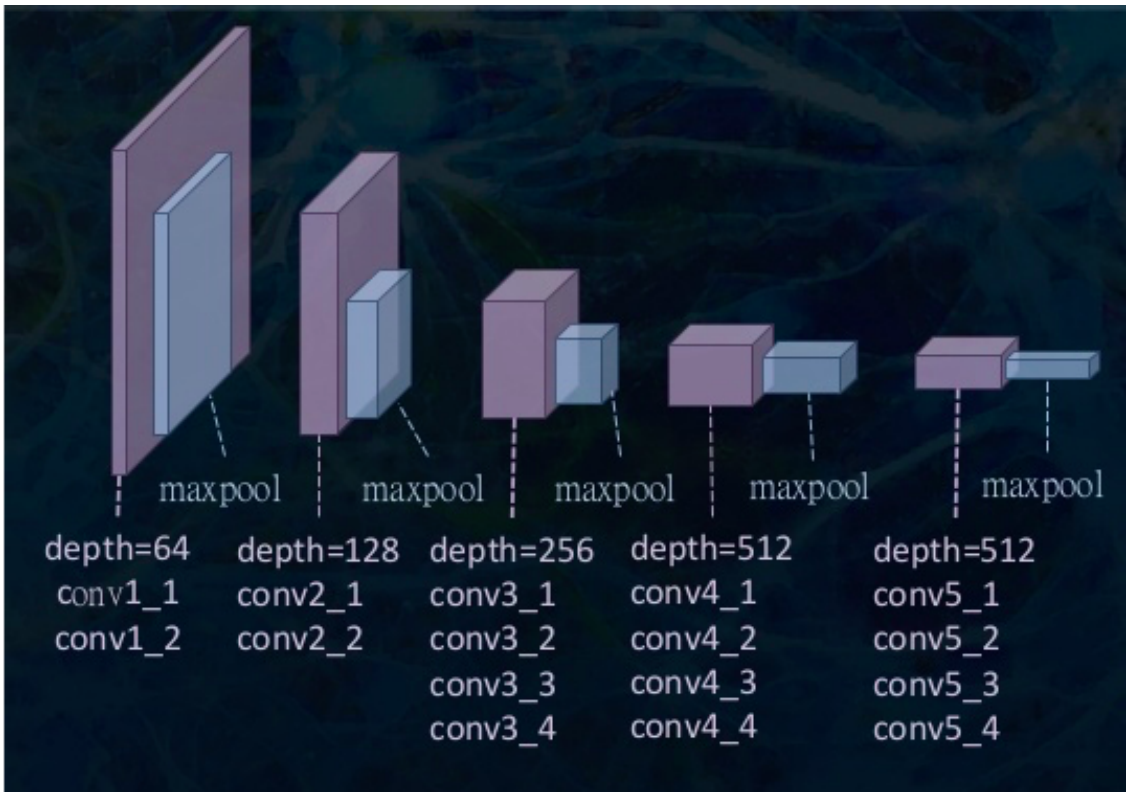
When solving classification problem for pictures it's important to choose suitable feature space F.

As soon as we determined feature space F and transformation $f: X \to F$, the problem we solve is simplified: find the algorithm $a: f(x) \mapsto y$, which generalizes the target function.

Advances in deep learning provide methods to solve the initial problem straightway, but we couldn't train the CNN due to lack of video card memory on our instance.

So, we decided to use spread pre-trained CNN output as that feature transform f.

We used VGG19 with reshaped input layer. Next we deleted everything after the convolutional layer and used that as features for the next processing. The structure of VGG19 that we used depictured further.



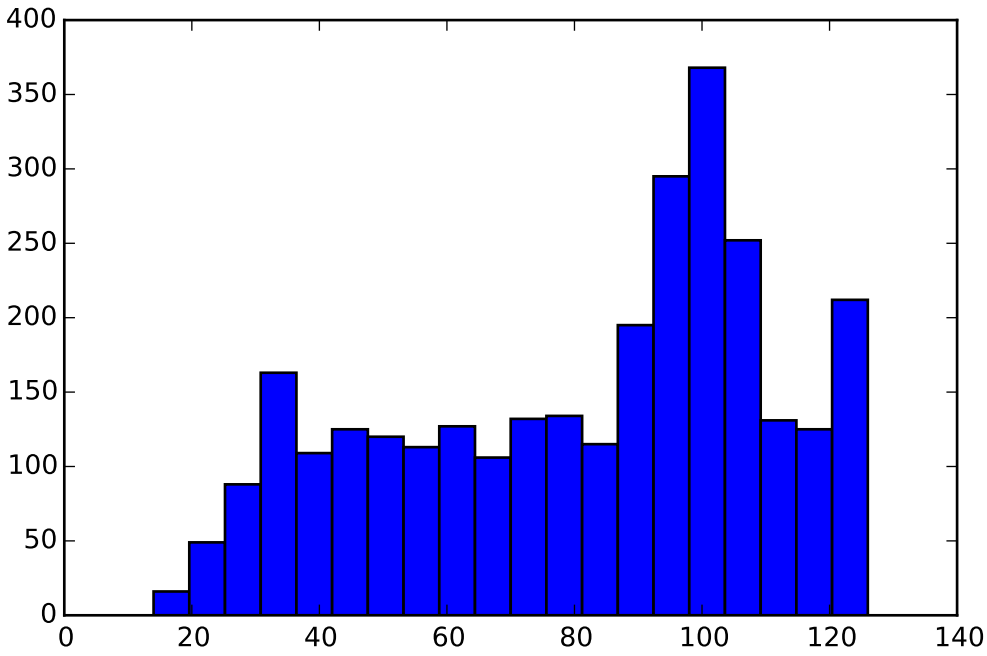
The result is a tensor of shape [512, 4, 9] raveled to the vector of length 18432.

6 Classification

We applied different methods to solve classification problem.

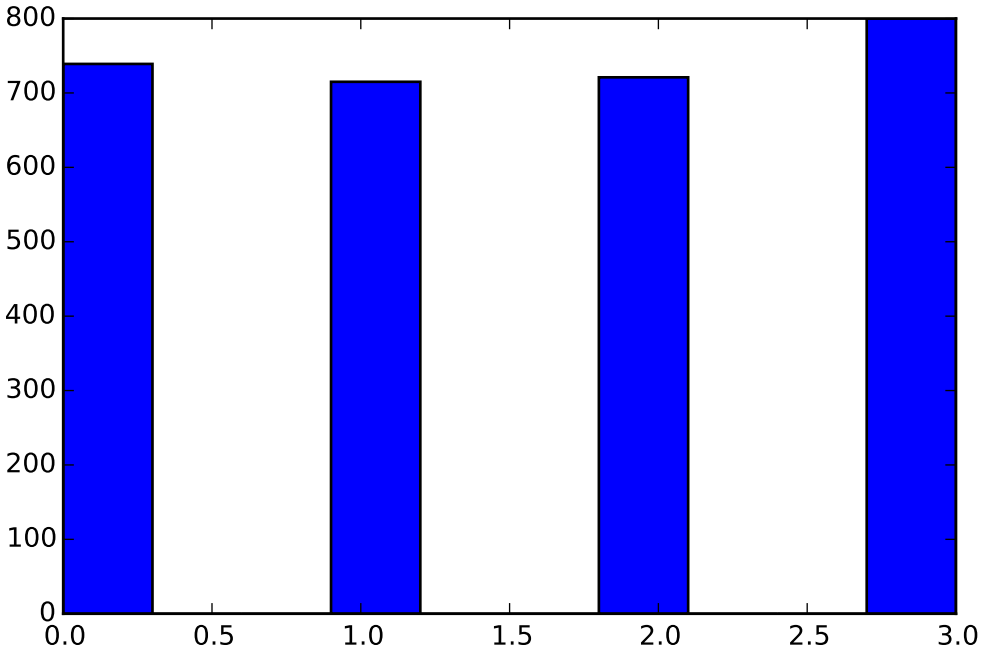
Cityscapes training set has 2975 samples. It's possible to use extra train dataset of about 20000 samples (see below).

```
In [5]: plt.hist(y_train, bins=20)

Out[5]: (array([  16.,   49.,   88.,  163.,  109.,  125.,  120.,  113.,  127.,
                 106.,  132.,  134.,  115.,  195.,  295.,  368.,  252.,  131.,
                 125.,  212.]),
         array([  14. ,   19.6,   25.2,   30.8,   36.4,   42. ,   47.6,   53.2,
                  58.8,   64.4,   70. ,   75.6,   81.2,   86.8,   92.4,   98. ,
                 103.6,  109.2,  114.8,  120.4,  126. ]),
         <a list of 20 Patch objects>)
```



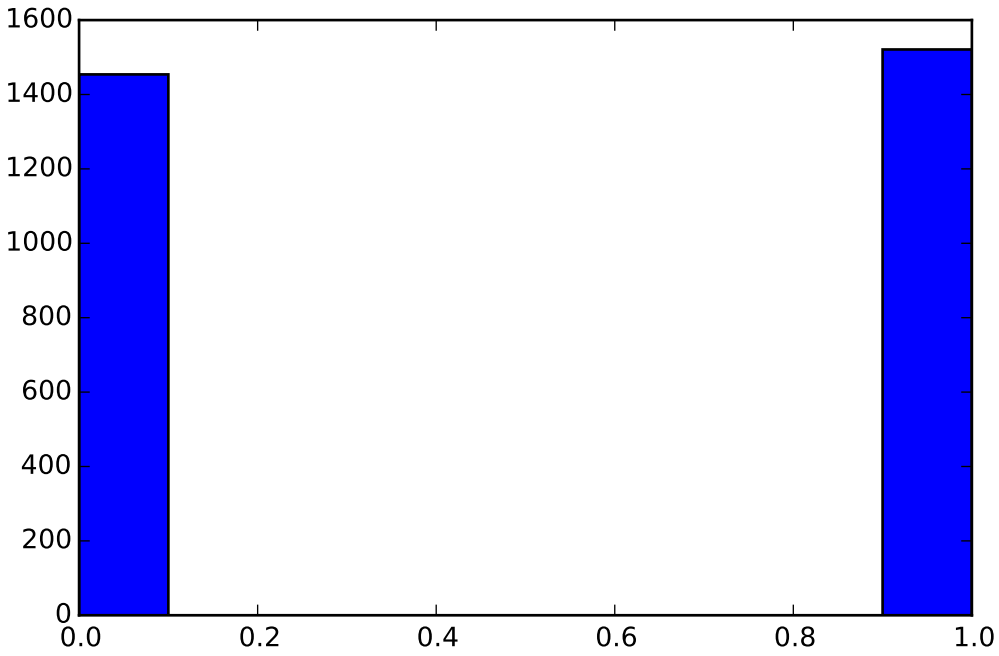

```
In [6]: len(y_train), y_train

Out[6]: (2975, array([86, 93, 43, ..., 39, 97, 95], dtype=uint8))

In [129]: bins = [np.percentile(y_train, 0),
                  np.percentile(y_train, 25),
                  np.percentile(y_train, 50),
                  np.percentile(y_train, 75),
                  np.percentile(y_train, 100) + 1]

In [130]: bins

Out[130]: [14.0, 57.0, 89.0, 103.0, 127.0]

In [131]: binary_bins = [np.percentile(y_train, 0),
                         np.percentile(y_train, 50),
                         np.percentile(y_train, 100) + 1]

In [132]: binary_bins

Out[132]: [14.0, 89.0, 127.0]

In [138]: y_train_binary = np.digitize(y_train, binary_bins) - 1
          y_val_binary = np.digitize(y_val, binary_bins) - 1
          y_test_binary = np.digitize(y_test, binary_bins) - 1

In [139]: y_train = np.digitize(y_train, bins) - 1
          y_val = np.digitize(y_val, bins) - 1
          y_test = np.digitize(y_test, bins) - 1

In [140]: plt.hist(y_train)
```

```
Out[140]: (array([ 739.,    0.,    0.,  715.,    0.,    0.,  721.,    0.,    0.,  800.]),
           array([ 0. ,  0.3,  0.6,  0.9,  1.2,  1.5,  1.8,  2.1,  2.4,  2.7,  3. ]),
           <a list of 10 Patch objects>)
```




```
In [141]: plt.hist(y_train_binary)
```

```
Out[141]: (array([ 1454.,     0.,     0.,     0.,     0.,     0.,     0.,     0.,
                      0.,  1521.]),
           array([ 0. ,  0.1,  0.2,  0.3,  0.4,  0.5,  0.6,  0.7,  0.8,  0.9,  1. ]),
           <a list of 10 Patch objects>)
```



6.1 Binary classification

```
In [142]: clf = LogisticRegression(C=0.01, penalty='l1')
          clf.fit(f1_train, y_train_binary).score(f1_val, y_val_binary)
```

```
Out[142]: 0.878
```

Let's move on to multi-class.

6.2 Multi-class

6.2.1 Simple models

```
In [28]: clf = LogisticRegression(C=0.01, penalty='l1')
         clf.fit(f1_train, y_train).score(f1_val, y_val)
```

```
Out[28]: 0.68000000000000005
```

```
In [14]: from sklearn.preprocessing import Normalizer

         normalizer = Normalizer().fit(f1_train)
         f1_train_normalized = normalizer.transform(f1_train)
         f1_val_normalized = normalizer.transform(f1_val)
```

```
In [66]: from sklearn.svm import LinearSVC

         clf = LinearSVC(C=1, penalty='l2', loss='squared_hinge', dual=True, multi_class='crammer_singe
         clf.fit(f1_train_normalized, y_train).score(f1_val_normalized, y_val)
```

```
Out[66]: 0.67000000000000004
```

```
In [55]: clf = LogisticRegression(C=8, penalty='l1')
         clf.fit(f1_train_normalized, y_train).score(f1_val_normalized, y_val)

Out[55]: 0.67000000000000004

In [60]: from sklearn.svm import SVC

         clf = SVC(C=1, kernel='rbf', gamma=1)
         clf.fit(f1_train_normalized, y_train).score(f1_val_normalized, y_val)

Out[60]: 0.66800000000000004

In [61]: from sklearn.svm import SVC

         clf = SVC(C=1, kernel='poly', gamma=1, degree=2)
         clf.fit(f1_train_normalized, y_train).score(f1_val_normalized, y_val)

Out[61]: 0.67400000000000004
```

6.2.2 Boosting

```
In [46]: from sklearn.decomposition import PCA

         pca = PCA(n_components=1000).fit(f1_train_normalized)

         f1_train_pca = pca.transform(f1_train_normalized)
         f1_val_pca = pca.transform(f1_val_normalized)

In [45]: from sklearn.ensemble import GradientBoostingClassifier

         GradientBoostingClassifier(n_estimators=200).fit(f1_train_pca, y_train).score(f1_val_pca, y_val

Out[45]: 0.59799999999999998
```

6.2.3 Stacking

```
In [76]: from stacking import Stacking

         basic_wildfowl = Stacking(base_estimators=[
                 (LogisticRegression(C=0.01, penalty='l1').fit,
                  lambda clf, X: clf.predict(X)),
                 (lambda X, y: LinearSVC(C=1, penalty='l2', loss='squared_hinge',
                                         dual=True, multi_class='crammer_singer').fit(normalizer.transf
                  lambda clf, X: clf.predict(normalizer.transform(X))),
                 (lambda X, y: LogisticRegression(C=8, penalty='l1').fit(normalizer.transform(X), y),
                  lambda clf, X: clf.predict(normalizer.transform(X))),
                 (lambda X, y: SVC(C=1, kernel='rbf', gamma=1).fit(normalizer.transform(X), y),
                  lambda clf, X: clf.predict(normalizer.transform(X))),
                 (lambda X, y: SVC(C=1, kernel='poly', gamma=1, degree=2).fit(normalizer.transform(X), y
                  lambda clf, X: clf.predict(normalizer.transform(X)))],
                             n_folds=5, extend_meta=False)
         basic_wildfowl.fit(np.array(f1_train), y_train)

/usr/lib64/python2.7/site-packages/sklearn/cross_validation.py:69: DeprecationWarning: The indices param
  stacklevel=1)
```

```
Out[76]: Stacking(base_estimators=[(<bound method LogisticRegression.fit of LogisticRegression(C=0.01, c
                    intercept_scaling=1, max_iter=100, multi_class='ovr',
                    penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
                    verbose=0)>, <f...on <lambda> at 0x1d848848>), (<function <lambda> at 0x1d848758>, <
               extend_meta=False, meta_fitter=None, n_folds=5)

In [77]: basic_wildfowl.fit_meta(SVC(C=5, kernel='poly', degree=2, gamma=1.).fit).score(np.array(f1_val

Out[77]: 0.68999999999999995

In [80]: basic_wildfowl.fit_meta(SVC(C=1, kernel='poly', degree=2, gamma=1.).fit).score(np.array(f1_val

Out[80]: 0.68999999999999995

In [81]: basic_wildfowl.fit_meta(SVC(C=10, kernel='poly', degree=2, gamma=1.).fit).score(np.array(f1_va

Out[81]: 0.68999999999999995

In [82]: basic_wildfowl.fit_meta(SVC(C=1, kernel='rbf', gamma=1.).fit).score(np.array(f1_val), y_val)

Out[82]: 0.69799999999999995

In [100]: basic_wildfowl.fit_meta(SVC(C=1, kernel='rbf', gamma=0.5).fit).score(np.array(f1_val), y_val)

Out[100]: 0.70399999999999996

In [109]: basic_wildfowl.fit_meta(SVC(C=1, kernel='rbf', gamma=0.3).fit).score(np.array(f1_val), y_val)

Out[109]: 0.70199999999999996

In [143]: basic_wildfowl.fit_meta(SVC(C=1, kernel='rbf', gamma=0.2).fit).score(np.array(f1_val), y_val)

Out[143]: 0.70599999999999996

In [105]: basic_wildfowl.fit_meta(SVC(C=1, kernel='rbf', gamma=0.1).fit).score(np.array(f1_val), y_val)

Out[105]: 0.70399999999999996

In [83]: basic_wildfowl.fit_meta(SVC(C=5, kernel='rbf', gamma=1.).fit).score(np.array(f1_val), y_val)

Out[83]: 0.69599999999999995

In [84]: basic_wildfowl.fit_meta(SVC(C=0.5, kernel='rbf', gamma=1.).fit).score(np.array(f1_val), y_val)

Out[84]: 0.69399999999999995

In [85]: basic_wildfowl.fit_meta(LogisticRegression(C=1, penalty='l1').fit).score(np.array(f1_val), y_va

Out[85]: 0.67000000000000004

In [89]: basic_wildfowl.fit_meta(LogisticRegression(C=10, penalty='l2').fit).score(np.array(f1_val), y_

Out[89]: 0.67000000000000004

In [92]: basic_wildfowl.fit_meta(RandomForestClassifier(n_estimators=100).fit).score(np.array(f1_val),

Out[92]: 0.69599999999999995

In [94]: basic_wildfowl.fit_meta(RandomForestClassifier(n_estimators=50, max_depth=10).fit).score(np.ar

Out[94]: 0.68999999999999995
```

```
In [95]: basic_wildfowl.fit_meta(RandomForestClassifier(n_estimators=50, max_depth=20).fit).score(np.ar

Out[95]: 0.69599999999999995

In [78]: basic_wildfowl.fit_meta(GradientBoostingClassifier(n_estimators=200).fit).score(np.array(f1_va

Out[78]: 0.69399999999999995

In [ ]: from sklearn.ensemble import AdaBoostClassifier

In [101]: basic_wildfowl.fit_meta(AdaBoostClassifier(n_estimators=30).fit).score(np.array(f1_val), y_va

Out[101]: 0.67000000000000004

In [96]: basic_wildfowl.fit_meta(AdaBoostClassifier(n_estimators=50).fit).score(np.array(f1_val), y_val

Out[96]: 0.68799999999999994

In [97]: basic_wildfowl.fit_meta(AdaBoostClassifier(n_estimators=100).fit).score(np.array(f1_val), y_va

Out[97]: 0.68000000000000005
```

6.2.4 With the road + segmentation

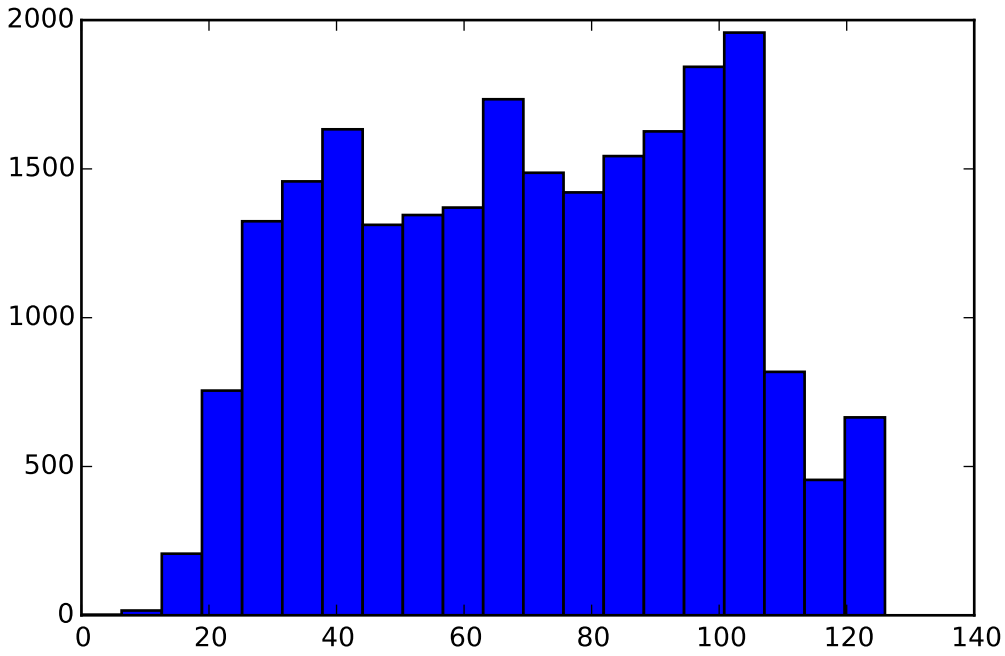
```
In [65]: clf = LogisticRegression(C=0.005, penalty='l1')
         clf.fit(np.hstack((np.array(f1_train), np.array(f2_train))), y_train).score(np.hstack((np.arra

Out[65]: 0.67600000000000005
```

6.2.5 Road deleted + segmentation

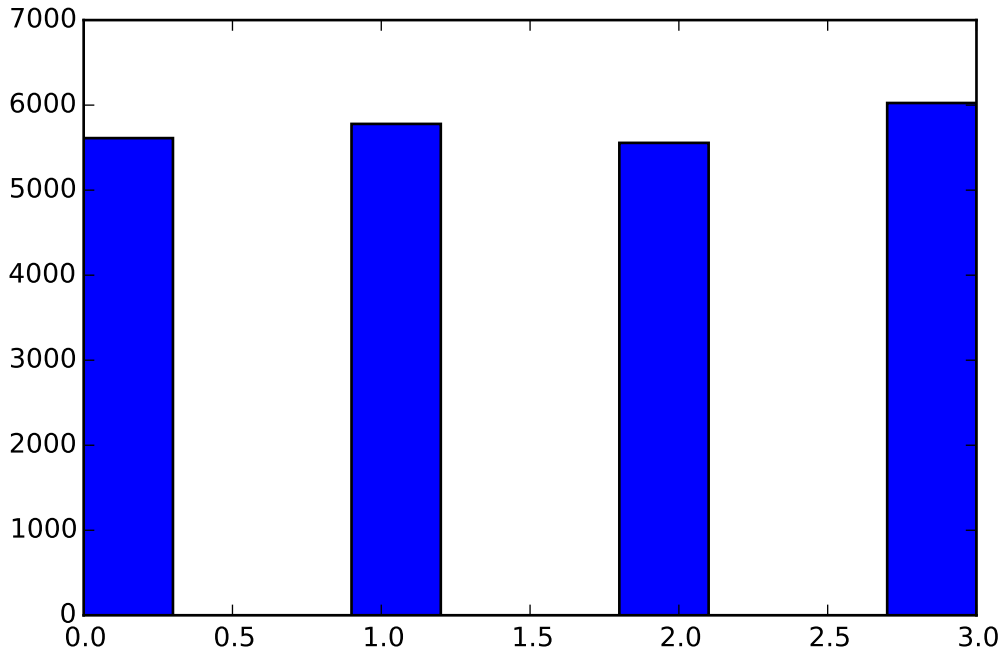
```
In [103]: clf = LogisticRegression(C=0.001, penalty='l1')
          clf.fit(np.hstack((np.array(f1_train), np.array(f2_train))), y_train).score(np.hstack((np.arr

Out[103]: 0.66600000000000004
```

6.2.6 Extra train dataset

```
In [161]: plt.hist(y_train, bins=20)

Out[161]: (array([    2.,    16.,   207.,   755.,  1324.,  1458.,  1633.,  1312.,
                  1345.,  1370.,  1734.,  1487.,  1421.,  1543.,  1626.,  1843.,
                  1958.,   818.,   455.,   665.]),
           array([   0. ,    6.3,   12.6,   18.9,   25.2,   31.5,   37.8,   44.1,
                    50.4,   56.7,   63. ,   69.3,   75.6,   81.9,   88.2,   94.5,
                   100.8,  107.1,  113.4,  119.7,  126. ]),
           <a list of 20 Patch objects>)
```




```
In [162]: bins_extra = [np.percentile(y_train, 0),
                        np.percentile(y_train, 25),
                        np.percentile(y_train, 50),
                        np.percentile(y_train, 75),
                        np.percentile(y_train, 100) + 1]

In [163]: bins_extra

Out[163]: [0.0, 46.0, 71.0, 94.0, 127.0]

In [164]: y_train = np.digitize(y_train, bins_extra) - 1
          y_val = np.digitize(y_val, bins_extra) - 1
          y_test = np.digitize(y_test, bins_extra) - 1

In [165]: plt.hist(y_train)

Out[165]: (array([ 5612.,     0.,     0.,  5779.,     0.,     0.,  5556.,     0.,
                      0.,  6025.]),
           array([ 0. ,  0.3,  0.6,  0.9,  1.2,  1.5,  1.8,  2.1,  2.4,  2.7,  3. ]),
           <a list of 10 Patch objects>)
```




```
In [ ]: clf = LogisticRegression(C=0.01, penalty='l1')
        clf.fit(f1_train, y_train).score(f1_val, y_val)
```

```
Out[ ]: 0.70199999999999996
```

One can see that using extra train dataset doesn't increase result significantly. It may be due to the fact that we did't have fine segmentation for extra train samples. Instead we had to use coarse segmentation of poor quality.

6.3 ANN

We tried the structure that follows the structure of VGG19. The difference was to add elu nonlinearities to all the dense layers. The structure is the following:

DenseLayer - 2048 units + elu
DropoutLayer - 50%
DenseLayer - 2048 units + elu
DropoutLayer - 50%
DenseLayer - 1024 units + elu
DropoutLayer - 50%
DenseLayer - 512 units + elu
DropoutLayer - 50%
DenseLayer - 256 units + elu
DropoutLayer - 50%
DenseLayer - Softmax

First we tried to add these layers to output of VGG19 features leayers. The problem was that it required much higher amount of memory and we couldn't use batches even of size 50. Next we used the described network as a separate classifier. It allowed us to use much higher batch sizes.

Furthermore we faced the problem of overfitting. In order to deal with that we introduced l2 ans l1 regularizations to the loss.

Talking about loss it is impotrant to mention that we decided to use categorical_crossentropy as a loss function. It was motivated by the fact that we dealed with different sizes of classes (we started with binary classification problem and went to 4 classes classification).

We had to play with regularization weights. Increasing and decreasing it we could limit overfiting and imrpove the loss on validation set.

6.3.1 Network deleted road, classes

```
In [37]: with open('data_rem_road.pkl', 'rb') as f:
             X_train, Seg_train, y_train, X_val, Seg_val, y_val, X_test, Seg_test, y_test = pickle.load

         with open('features_rem_road.pkl', 'rb') as f:
             f1_train, f1_val, f1_test, f2_train, f2_val, f2_test = pickle.load(f)

         bins = [np.percentile(y_train, 0),
                 np.percentile(y_train, 25),
                 np.percentile(y_train, 50),
                 np.percentile(y_train, 75),
                 np.percentile(y_train, 100) + 1]

         y_train = np.digitize(y_train, bins) - 1
         y_val = np.digitize(y_val, bins) - 1
         y_test = np.digitize(y_test, bins) - 1

         input_layer = InputLayer((None, f1_train[0].shape[0]))
         ll1 = DenseLayer(input_layer, num_units=2048, nonlinearity=lasagne.nonlinearities.elu)
         dr1 = DropoutLayer(ll1, p=0.5)
         ll2 = DenseLayer(dr1, num_units=2048, nonlinearity=lasagne.nonlinearities.elu)
         dr3 = DropoutLayer(ll2, p=0.5)
         ll3 = DenseLayer(dr3, num_units=1024, nonlinearity=lasagne.nonlinearities.elu)
         dr4 = DropoutLayer(ll3, p=0.5)
         ll4 = DenseLayer(dr4, num_units=512, nonlinearity=lasagne.nonlinearities.elu)
         dr5 = DropoutLayer(ll4, p=0.5)
         ll5 = DenseLayer(dr5, num_units=256, nonlinearity=lasagne.nonlinearities.elu)
         dr6 = DropoutLayer(ll5, p=0.5)
         percentile = DenseLayer(dr6, num_units=len(set(y_train)), nonlinearity=softmax)

         target_y = T.vector("target Y integer", dtype='int32')
         input_X = T.matrix('X')

         probs = lasagne.layers.get_output(percentile, input_X, deterministic = True)
         y_predicted = np.argmax(probs, axis=1)

         #all network weights (shared variables)
         all_weights = lasagne.layers.get_all_params(percentile)
         print(all_weights)

         #Mean categorical crossentropy as a loss function - similar to logistic loss but for multiclas
         loss = lasagne.objectives.categorical_crossentropy(probs, target_y).mean()
         l2_penalty = regularize_layer_params(percentile, l2) * 1e-1
         l1_penalty = regularize_layer_params(percentile, l1) * 1e-3
         loss += l2_penalty + l1_penalty

         #prediction accuracy
```

```
        accuracy = lasagne.objectives.categorical_accuracy(probs, target_y).mean()

        #This function computes gradient AND composes weight updates just like you did earlier
        updates_sgd = lasagne.updates.adagrad(loss, all_weights, learning_rate=0.01)

        #function that computes loss and updates weights
        train_fun = theano.function([input_X, target_y], [loss, accuracy], updates = updates_sgd)

        #function that just computes accuracy
        accuracy_fun = theano.function([input_X, target_y],accuracy)

        num_epochs = 30 #amount of passes through the data

        batch_size = 100 #number of samples processed at each function call

        for epoch in range(num_epochs):
            # In each epoch, we do a full pass over the training data:
            train_err = 0
            train_acc = 0
            train_batches = 0
            start_time = time.time()
            for batch in iterate_minibatches(f1_train, y_train, batch_size):
                inputs, targets = batch
                train_err_batch, train_acc_batch = train_fun(inputs, targets.astype(np.int32))
                train_err += train_err_batch
                train_acc += train_acc_batch
                train_batches += 1

            # And a full pass over the validation data:
            val_acc = 0
            val_batches = 0
            for batch in iterate_minibatches(f1_val, y_val, batch_size):
                inputs, targets = batch
                val_acc += accuracy_fun(inputs, targets.astype(np.int32))
                val_batches += 1


            # Then we print the results for this epoch:
            print("Epoch {} of {} took {:.3f}s".format(
                epoch + 1, num_epochs, time.time() - start_time))

            print("  training loss (in-iteration):\t\t{:.6f}".format(train_err / train_batches))
            print("  train accuracy:\t\t{:.2f} %".format(
                train_acc / train_batches * 100))
            print("  validation accuracy:\t\t{:.2f} %".format(
                val_acc / val_batches * 100))
```

```
[W, b, W, b, W, b, W, b, W, b, W, b]
Epoch 1 of 30 took 1.998s
  training loss (in-iteration):                3749.619600
  train accuracy:                28.59 %
  validation accuracy:                26.00 %
Epoch 2 of 30 took 2.015s
  training loss (in-iteration):                3.113019
```

```
  train accuracy:                32.24 %
  validation accuracy:                46.60 %
Epoch 3 of 30 took 1.982s
  training loss (in-iteration):                2.176733
  train accuracy:                45.90 %
  validation accuracy:                49.40 %
Epoch 4 of 30 took 2.010s
  training loss (in-iteration):                1.896570
  train accuracy:                52.72 %
  validation accuracy:                58.00 %
Epoch 5 of 30 took 1.978s
  training loss (in-iteration):                1.765641
  train accuracy:                58.38 %
  validation accuracy:                52.20 %
Epoch 6 of 30 took 2.000s
  training loss (in-iteration):                1.671071
  train accuracy:                63.17 %
  validation accuracy:                62.00 %
Epoch 7 of 30 took 2.000s
  training loss (in-iteration):                1.551463
  train accuracy:                69.31 %
  validation accuracy:                55.20 %
Epoch 8 of 30 took 2.111s
  training loss (in-iteration):                1.477413
  train accuracy:                71.52 %
  validation accuracy:                66.60 %
Epoch 9 of 30 took 2.005s
  training loss (in-iteration):                1.404215
  train accuracy:                76.62 %
  validation accuracy:                59.40 %
Epoch 10 of 30 took 1.980s
  training loss (in-iteration):                1.373313
  train accuracy:                76.55 %
  validation accuracy:                67.40 %
Epoch 11 of 30 took 1.987s
  training loss (in-iteration):                1.343516
  train accuracy:                77.24 %
  validation accuracy:                60.80 %
Epoch 12 of 30 took 2.008s
  training loss (in-iteration):                1.256678
  train accuracy:                81.34 %
  validation accuracy:                61.20 %
Epoch 13 of 30 took 2.102s
  training loss (in-iteration):                1.214769
  train accuracy:                83.93 %
  validation accuracy:                66.20 %
Epoch 14 of 30 took 1.999s
  training loss (in-iteration):                1.203365
  train accuracy:                84.66 %
  validation accuracy:                61.60 %
Epoch 15 of 30 took 1.974s
  training loss (in-iteration):                1.129455
  train accuracy:                87.41 %
  validation accuracy:                67.00 %
```

```
Epoch 16 of 30 took 2.126s
  training loss (in-iteration):                1.263559
  train accuracy:                85.00 %
  validation accuracy:                67.40 %
Epoch 17 of 30 took 1.980s
  training loss (in-iteration):                1.062010
  train accuracy:                91.52 %
  validation accuracy:                65.40 %
Epoch 18 of 30 took 1.974s
  training loss (in-iteration):                1.000695
  train accuracy:                93.72 %
  validation accuracy:                64.40 %
Epoch 19 of 30 took 2.005s
  training loss (in-iteration):                0.974304
  train accuracy:                94.59 %
  validation accuracy:                64.00 %
Epoch 20 of 30 took 1.980s
  training loss (in-iteration):                0.925185
  train accuracy:                96.62 %
  validation accuracy:                62.00 %
Epoch 21 of 30 took 2.003s
  training loss (in-iteration):                0.937583
  train accuracy:                96.28 %
  validation accuracy:                62.60 %
Epoch 22 of 30 took 1.997s
  training loss (in-iteration):                1.025416
  train accuracy:                93.21 %
  validation accuracy:                62.00 %
Epoch 23 of 30 took 1.987s
  training loss (in-iteration):                1.056850
  train accuracy:                92.55 %
  validation accuracy:                63.80 %
Epoch 24 of 30 took 1.997s
  training loss (in-iteration):                0.880320
  train accuracy:                98.07 %
  validation accuracy:                64.40 %
Epoch 25 of 30 took 2.182s
  training loss (in-iteration):                0.861131
  train accuracy:                98.76 %
  validation accuracy:                64.80 %
Epoch 26 of 30 took 2.169s
  training loss (in-iteration):                0.866686
  train accuracy:                98.07 %
  validation accuracy:                64.60 %
Epoch 27 of 30 took 2.097s
  training loss (in-iteration):                0.839886
  train accuracy:                99.03 %
  validation accuracy:                64.80 %
```

```
KeyboardInterrupt                         Traceback (most recent call last)
```

```
    <ipython-input-37-d82e6a4058e4> in <module>()
     68     for batch in iterate_minibatches(f1_train, y_train, batch_size):
     69         inputs, targets = batch
---> 70         train_err_batch, train_acc_batch = train_fun(inputs, targets.astype(np.int32))
     71         train_err += train_err_batch
     72         train_acc += train_acc_batch


    /usr/lib/python2.7/site-packages/theano/compile/function_module.pyc in __call__(self, *args, **kw
    813                         s.storage[0] = s.type.filter(
    814                             arg, strict=s.strict,
--> 815                             allow_downcast=s.allow_downcast)
    816
    817                     except Exception as e:


    /usr/lib/python2.7/site-packages/theano/tensor/type.pyc in filter(self, data, strict, allow_down
    148                     # data has to be converted.
    149                     # Check that this conversion is lossless
--> 150                     converted_data = theano._asarray(data, self.dtype)
    151                     # We use the `values_eq` static function from TensorType
    152                     # to handle NaN values.


    /usr/lib/python2.7/site-packages/theano/misc/safe_asarray.pyc in _asarray(a, dtype, order)
     32         dtype = theano.config.floatX
     33     dtype = numpy.dtype(dtype)  # Convert into dtype object.
---> 34     rval = numpy.asarray(a, dtype=dtype, order=order)
     35     # Note that dtype comparison must be done by comparing their `num`
     36     # attribute. One cannot assume that two identical data types are pointers


    /usr/lib64/python2.7/site-packages/numpy/core/numeric.pyc in asarray(a, dtype, order)
    480
    481     """
--> 482     return array(a, dtype, copy=False, order=order)
    483
    484 def asanyarray(a, dtype=None, order=None):


    KeyboardInterrupt:
```

6.3.2 Network with road, 4 classes

```
In [ ]: with open('data_basic.pkl', 'rb') as f:
            X_train, Seg_train, y_train, X_val, Seg_val, y_val, X_test, Seg_test, y_test = pickle.load(

        with open('features_basic.pkl', 'rb') as f:
            f1_train, f1_val, f1_test, f2_train, f2_val, f2_test = pickle.load(f)

        bins = [np.percentile(y_train, 0),
                np.percentile(y_train, 25),
                np.percentile(y_train, 50),
```

```
        np.percentile(y_train, 75),
        np.percentile(y_train, 100) + 1]

    y_train = np.digitize(y_train, bins) - 1
    y_val = np.digitize(y_val, bins) - 1
    y_test = np.digitize(y_test, bins) - 1
```

In [36]:
```
input_layer = InputLayer((None, f1_train[0].shape[0]))
ll1 = DenseLayer(input_layer, num_units=2048, nonlinearity=lasagne.nonlinearities.elu)
dr1 = DropoutLayer(ll1, p=0.5)
ll2 = DenseLayer(dr1, num_units=2048, nonlinearity=lasagne.nonlinearities.elu)
dr3 = DropoutLayer(ll2, p=0.5)
ll3 = DenseLayer(dr3, num_units=1024, nonlinearity=lasagne.nonlinearities.elu)
dr4 = DropoutLayer(ll3, p=0.5)
ll4 = DenseLayer(dr4, num_units=512, nonlinearity=lasagne.nonlinearities.elu)
dr5 = DropoutLayer(ll4, p=0.5)
ll5 = DenseLayer(dr5, num_units=256, nonlinearity=lasagne.nonlinearities.elu)
dr6 = DropoutLayer(ll5, p=0.5)
percentile = DenseLayer(dr6, num_units=len(set(y_train)), nonlinearity=softmax)

target_y = T.vector("target Y integer", dtype='int32')
input_X = T.matrix('X')

probs = lasagne.layers.get_output(percentile, input_X, deterministic = True)
y_predicted = np.argmax(probs, axis=1)

#all network weights (shared variables)
all_weights = lasagne.layers.get_all_params(percentile)
print(all_weights)

#Mean categorical crossentropy as a loss function - similar to logistic loss but for multiclas
loss = lasagne.objectives.categorical_crossentropy(probs, target_y).mean()
l2_penalty = regularize_layer_params(percentile, l2) * 1e-1
l1_penalty = regularize_layer_params(percentile, l1) * 1e-2
loss += l2_penalty + l1_penalty

#prediction accuracy
accuracy = lasagne.objectives.categorical_accuracy(probs, target_y).mean()

#This function computes gradient AND composes weight updates just like you did earlier
updates_sgd = lasagne.updates.adagrad(loss, all_weights, learning_rate=0.005)

#function that computes loss and updates weights
train_fun = theano.function([input_X, target_y], [loss, accuracy], updates = updates_sgd)

#function that just computes accuracy
accuracy_fun = theano.function([input_X, target_y],accuracy)

num_epochs = 300 #amount of passes through the data

batch_size = 100 #number of samples processed at each function call

for epoch in range(num_epochs):
    # In each epoch, we do a full pass over the training data:
```

```
            train_err = 0
            train_acc = 0
            train_batches = 0
            start_time = time.time()
            for batch in iterate_minibatches(f1_train, y_train, batch_size):
                inputs, targets = batch
                train_err_batch, train_acc_batch = train_fun(inputs, targets.astype(np.int32))
                train_err += train_err_batch
                train_acc += train_acc_batch
                train_batches += 1

            # And a full pass over the validation data:
            val_acc = 0
            val_batches = 0
            for batch in iterate_minibatches(f1_val, y_val, batch_size):
                inputs, targets = batch
                val_acc += accuracy_fun(inputs, targets.astype(np.int32))
                val_batches += 1


            # Then we print the results for this epoch:
            print("Epoch {} of {} took {:.3f}s".format(
                epoch + 1, num_epochs, time.time() - start_time))

            print("  training loss (in-iteration):\t\t{:.6f}".format(train_err / train_batches))
            print("  train accuracy:\t\t{:.2f} %".format(
                train_acc / train_batches * 100))
            print("  validation accuracy:\t\t{:.2f} %".format(
                val_acc / val_batches * 100))
```

```
[W, b, W, b, W, b, W, b, W, b, W, b]
Epoch 1 of 300 took 2.036s
  training loss (in-iteration):                 140.387504
  train accuracy:                 31.28 %
  validation accuracy:                 52.80 %
Epoch 2 of 300 took 2.016s
  training loss (in-iteration):                 13.295092
  train accuracy:                 55.17 %
  validation accuracy:                 58.20 %
Epoch 3 of 300 took 2.002s
  training loss (in-iteration):                 12.705572
  train accuracy:                 62.45 %
  validation accuracy:                 60.40 %
Epoch 4 of 300 took 2.003s
  training loss (in-iteration):                 12.226186
  train accuracy:                 68.86 %
  validation accuracy:                 60.40 %
Epoch 5 of 300 took 2.002s
  training loss (in-iteration):                 11.880651
  train accuracy:                 71.07 %
  validation accuracy:                 60.20 %
Epoch 6 of 300 took 2.014s
  training loss (in-iteration):                 11.404465
  train accuracy:                 79.07 %
```

```
  validation accuracy:               61.80 %
Epoch 7 of 300 took 2.018s
  training loss (in-iteration):                11.053822
  train accuracy:                84.86 %
  validation accuracy:               65.00 %
Epoch 8 of 300 took 1.896s
  training loss (in-iteration):                10.977491
  train accuracy:                79.59 %
  validation accuracy:               61.00 %
Epoch 9 of 300 took 2.035s
  training loss (in-iteration):                10.554585
  train accuracy:                87.14 %
  validation accuracy:               65.00 %
Epoch 10 of 300 took 1.963s
  training loss (in-iteration):                10.316450
  train accuracy:                90.83 %
  validation accuracy:               64.80 %
Epoch 11 of 300 took 1.936s
  training loss (in-iteration):                10.013761
  train accuracy:                95.55 %
  validation accuracy:               63.40 %
Epoch 12 of 300 took 1.933s
  training loss (in-iteration):                9.810423
  train accuracy:                97.24 %
  validation accuracy:               63.80 %
Epoch 13 of 300 took 1.933s
  training loss (in-iteration):                9.722251
  train accuracy:                95.52 %
  validation accuracy:               63.00 %
Epoch 14 of 300 took 1.922s
  training loss (in-iteration):                9.467655
  train accuracy:                99.24 %
  validation accuracy:               64.40 %
Epoch 15 of 300 took 1.951s
  training loss (in-iteration):                9.321485
  train accuracy:                99.38 %
  validation accuracy:               66.20 %
Epoch 16 of 300 took 1.924s
  training loss (in-iteration):                9.184269
  train accuracy:                99.72 %
  validation accuracy:               65.60 %
Epoch 17 of 300 took 1.955s
  training loss (in-iteration):                9.060074
  train accuracy:                99.86 %
  validation accuracy:               65.60 %
Epoch 18 of 300 took 2.053s
  training loss (in-iteration):                8.943007
  train accuracy:                99.93 %
  validation accuracy:               64.40 %
```

```
KeyboardInterrupt                         Traceback (most recent call last)
```

```
<ipython-input-36-c68afadbdafd> in <module>()
 52     for batch in iterate_minibatches(f1_train, y_train, batch_size):
 53         inputs, targets = batch
---> 54         train_err_batch, train_acc_batch = train_fun(inputs, targets.astype(np.int32))
 55         train_err += train_err_batch
 56         train_acc += train_acc_batch


/usr/lib/python2.7/site-packages/theano/compile/function_module.pyc in __call__(self, *args, **kw
887         try:
888             outputs =\
--> 889                 self.fn() if output_subset is None else\
890                 self.fn(output_subset=output_subset)
891         except Exception:


KeyboardInterrupt:
```

6.3.3 Network deleted road, 4 classes, stacked with segs

```
In [9]: with open('data_rem_road.pkl', 'rb') as f:
            X_train, Seg_train, y_train, X_val, Seg_val, y_val, X_test, Seg_test, y_test = pickle.load(

        with open('features_rem_road.pkl', 'rb') as f:
            f1_train, f1_val, f1_test, f2_train, f2_val, f2_test = pickle.load(f)

        f1_train = np.hstack((np.array(f1_train), np.array(f2_train)))
        f1_val = np.hstack((np.array(f1_val), np.array(f2_val)))

        bins = [np.percentile(y_train, 0),
                np.percentile(y_train, 25),
                np.percentile(y_train, 50),
                np.percentile(y_train, 75),
                np.percentile(y_train, 100) + 1]

        y_train = np.digitize(y_train, bins) - 1
        y_val = np.digitize(y_val, bins) - 1
        y_test = np.digitize(y_test, bins) - 1

        input_layer = InputLayer((None, f1_train[0].shape[0]))
        ll1 = DenseLayer(input_layer, num_units=4096)
        dr1 = DropoutLayer(ll1, p=0.5)
        ll2 = DenseLayer(dr1, num_units=4096)
        dr3 = DropoutLayer(ll2, p=0.5)
        percentile = DenseLayer(dr3, num_units=len(set(y_train)), nonlinearity=softmax)

        target_y = T.vector("target Y integer", dtype='int32')
        input_X = T.matrix('X')

        probs = lasagne.layers.get_output(percentile, input_X, deterministic = True)
        y_predicted = np.argmax(probs, axis=1)
```

```
#all network weights (shared variables)
all_weights = lasagne.layers.get_all_params(percentile)
print(all_weights)

#Mean categorical crossentropy as a loss function - similar to logistic loss but for multiclass
loss = lasagne.objectives.categorical_crossentropy(probs, target_y).mean()
l2_penalty = regularize_layer_params(percentile, l2) * 1e-2
l1_penalty = regularize_layer_params(percentile, l1) * 1e-3
loss += l2_penalty + l1_penalty

#prediction accuracy
accuracy = lasagne.objectives.categorical_accuracy(probs, target_y).mean()

#This function computes gradient AND composes weight updates just like you did earlier
updates_sgd = lasagne.updates.adagrad(loss, all_weights, learning_rate=0.01)

#function that computes loss and updates weights
train_fun = theano.function([input_X, target_y], [loss, accuracy], updates = updates_sgd)

#function that just computes accuracy
accuracy_fun = theano.function([input_X, target_y],accuracy)

num_epochs = 30 #amount of passes through the data

batch_size = 100 #number of samples processed at each function call

for epoch in range(num_epochs):
    # In each epoch, we do a full pass over the training data:
    train_err = 0
    train_acc = 0
    train_batches = 0
    start_time = time.time()
    for batch in iterate_minibatches(f1_train, y_train, batch_size):
        inputs, targets = batch
        train_err_batch, train_acc_batch = train_fun(inputs, targets.astype(np.int32))
        train_err += train_err_batch
        train_acc += train_acc_batch
        train_batches += 1

    # And a full pass over the validation data:
    val_acc = 0
    val_batches = 0
    for batch in iterate_minibatches(f1_val, y_val, batch_size):
        inputs, targets = batch
        val_acc += accuracy_fun(inputs, targets.astype(np.int32))
        val_batches += 1


    # Then we print the results for this epoch:
    print("Epoch {} of {} took {:.3f}s".format(
        epoch + 1, num_epochs, time.time() - start_time))

    print("  training loss (in-iteration):\t\t{:.6f}".format(train_err / train_batches))
    print("  train accuracy:\t\t{:.2f} %".format(
```

```
            train_acc / train_batches * 100))
        print("  validation accuracy:\t\t{:.2f} %".format(
            val_acc / val_batches * 100))
```

```
[W, b, W, b, W, b]
```

```
---------------------------------------------------------------------------

MemoryError                               Traceback (most recent call last)

<ipython-input-9-7a80a87eb928> in <module>()
     65     for batch in iterate_minibatches(f1_train, y_train, batch_size):
     66         inputs, targets = batch
---> 67         train_err_batch, train_acc_batch = train_fun(inputs, targets.astype(np.int32))
     68         train_err += train_err_batch
     69         train_acc += train_acc_batch


/home/user/anaconda2/lib/python2.7/site-packages/theano/compile/function_module.pyc in __call__(s
    910                     node=self.fn.nodes[self.fn.position_of_error],
    911                     thunk=thunk,
--> 912                     storage_map=getattr(self.fn, 'storage_map', None))
    913             else:
    914                 # old-style linkers raise their own exceptions


/home/user/anaconda2/lib/python2.7/site-packages/theano/gof/link.pyc in raise_with_op(node, thun
    312         # extra long error message in that case.
    313         pass
--> 314     reraise(exc_type, exc_value, exc_trace)
    315
    316


/home/user/anaconda2/lib/python2.7/site-packages/theano/compile/function_module.pyc in __call__(s
    897         try:
    898             outputs =\
--> 899                 self.fn() if output_subset is None else\
    900                 self.fn(output_subset=output_subset)
    901         except Exception:


MemoryError: Error allocating 603979776 bytes of device memory (out of memory).
Apply node that caused the error: GpuDot22(GpuDimShuffle{1,0}.0, GpuElemwise{Composite{(i0 + (i0 * s
Toposort index: 54
Inputs types: [CudaNdarrayType(float32, matrix), CudaNdarrayType(float32, matrix)]
Inputs shapes: [(36864, 100), (100, 4096)]
Inputs strides: [(1, 36864), (4096, 1)]
Inputs values: ['not shown', 'not shown']
Outputs clients: [[GpuElemwise{Sqr}[(0, 0)](GpuDot22.0)]]

HINT: Re-running with most Theano optimization disabled could give you a back-trace of when this no
HINT: Use the Theano flag 'exception_verbosity=high' for a debugprint and storage map footprint of t
```

6.3.4 Network with road, 4 classes, stacked with segs

In [8]:
```
with open('data_basic.pkl', 'rb') as f:
    X_train, Seg_train, y_train, X_val, Seg_val, y_val, X_test, Seg_test, y_test = pickle.load(

with open('features_basic.pkl', 'rb') as f:
    f1_train, f1_val, f1_test, f2_train, f2_val, f2_test = pickle.load(f)

f1_train = np.hstack((np.array(f1_train), np.array(f2_train)))
f1_val = np.hstack((np.array(f1_val), np.array(f2_val)))

bins = [np.percentile(y_train, 0),
        np.percentile(y_train, 25),
        np.percentile(y_train, 50),
        np.percentile(y_train, 75),
        np.percentile(y_train, 100) + 1]

y_train = np.digitize(y_train, bins) - 1
y_val = np.digitize(y_val, bins) - 1
y_test = np.digitize(y_test, bins) - 1

input_layer = InputLayer((None, f1_train[0].shape[0]))
l1 = DenseLayer(input_layer, num_units=4096)
dr1 = DropoutLayer(l1, p=0.5)
l2 = DenseLayer(dr1, num_units=4096)
dr3 = DropoutLayer(l2, p=0.5)
percentile = DenseLayer(dr3, num_units=len(set(y_train)), nonlinearity=softmax)

target_y = T.vector("target Y integer", dtype='int32')
input_X = T.matrix('X')

probs = lasagne.layers.get_output(percentile, input_X, deterministic = True)
y_predicted = np.argmax(probs, axis=1)

#all network weights (shared variables)
all_weights = lasagne.layers.get_all_params(percentile)
print(all_weights)

#Mean categorical crossentropy as a loss function - similar to logistic loss but for multiclass
loss = lasagne.objectives.categorical_crossentropy(probs, target_y).mean()
l2_penalty = regularize_layer_params(percentile, l2) * 1e-1
l1_penalty = regularize_layer_params(percentile, l1) * 1e-2
loss += l2_penalty + l1_penalty

#prediction accuracy
accuracy = lasagne.objectives.categorical_accuracy(probs, target_y).mean()

#This function computes gradient AND composes weight updates just like you did earlier
updates_sgd = lasagne.updates.adagrad(loss, all_weights, learning_rate=0.01)

#function that computes loss and updates weights
train_fun = theano.function([input_X, target_y], [loss, accuracy], updates = updates_sgd)

#function that just computes accuracy
```

```
        accuracy_fun = theano.function([input_X, target_y],accuracy)

        num_epochs = 30 #amount of passes through the data

        batch_size = 100 #number of samples processed at each function call

        for epoch in range(num_epochs):
            # In each epoch, we do a full pass over the training data:
            train_err = 0
            train_acc = 0
            train_batches = 0
            start_time = time.time()
            for batch in iterate_minibatches(f1_train, y_train, batch_size):
                inputs, targets = batch
                train_err_batch, train_acc_batch = train_fun(inputs, targets.astype(np.int32))
                train_err += train_err_batch
                train_acc += train_acc_batch
                train_batches += 1

            # And a full pass over the validation data:
            val_acc = 0
            val_batches = 0
            for batch in iterate_minibatches(f1_val, y_val, batch_size):
                inputs, targets = batch
                val_acc += accuracy_fun(inputs, targets.astype(np.int32))
                val_batches += 1


            # Then we print the results for this epoch:
            print("Epoch {} of {} took {:.3f}s".format(
                epoch + 1, num_epochs, time.time() - start_time))

            print("  training loss (in-iteration):\t\t{:.6f}".format(train_err / train_batches))
            print("  train accuracy:\t\t{:.2f} %".format(
                train_acc / train_batches * 100))
            print("  validation accuracy:\t\t{:.2f} %".format(
                val_acc / val_batches * 100))
```

```
[W, b, W, b, W, b]
Epoch 1 of 30 took 4.315s
  training loss (in-iteration):                 4726.092065
  train accuracy:                24.38 %
  validation accuracy:                33.00 %
Epoch 2 of 30 took 4.367s
  training loss (in-iteration):                 11.885494
  train accuracy:                30.03 %
  validation accuracy:                26.00 %
Epoch 3 of 30 took 4.157s
  training loss (in-iteration):                 5.118199
  train accuracy:                30.03 %
  validation accuracy:                25.20 %
Epoch 4 of 30 took 4.156s
  training loss (in-iteration):                 4.719048
  train accuracy:                33.24 %
```

```
  validation accuracy:                25.00 %
Epoch 5 of 30 took 4.154s
  training loss (in-iteration):                4.602650
  train accuracy:                33.83 %
  validation accuracy:                25.40 %
Epoch 6 of 30 took 4.158s
  training loss (in-iteration):                4.511264
  train accuracy:                34.45 %
  validation accuracy:                29.20 %
Epoch 7 of 30 took 4.156s
  training loss (in-iteration):                4.433514
  train accuracy:                35.31 %
  validation accuracy:                31.80 %
Epoch 8 of 30 took 4.153s
  training loss (in-iteration):                4.364174
  train accuracy:                35.90 %
  validation accuracy:                33.00 %
Epoch 9 of 30 took 4.321s
  training loss (in-iteration):                4.301553
  train accuracy:                36.66 %
  validation accuracy:                34.60 %
Epoch 10 of 30 took 4.163s
  training loss (in-iteration):                4.242831
  train accuracy:                38.03 %
  validation accuracy:                36.00 %
Epoch 11 of 30 took 4.158s
  training loss (in-iteration):                4.186211
  train accuracy:                40.17 %
  validation accuracy:                37.40 %
Epoch 12 of 30 took 4.189s
  training loss (in-iteration):                4.131390
  train accuracy:                42.07 %
  validation accuracy:                37.60 %
Epoch 13 of 30 took 4.163s
  training loss (in-iteration):                4.075547
  train accuracy:                43.79 %
  validation accuracy:                39.00 %
Epoch 14 of 30 took 4.183s
  training loss (in-iteration):                4.020848
  train accuracy:                45.31 %
  validation accuracy:                40.00 %
Epoch 15 of 30 took 4.165s
  training loss (in-iteration):                3.965067
  train accuracy:                47.62 %
  validation accuracy:                42.20 %
Epoch 16 of 30 took 4.164s
  training loss (in-iteration):                3.908799
  train accuracy:                50.52 %
  validation accuracy:                42.60 %
Epoch 17 of 30 took 4.170s
  training loss (in-iteration):                3.857314
  train accuracy:                53.24 %
  validation accuracy:                43.60 %
Epoch 18 of 30 took 4.167s
```

```
  training loss (in-iteration):                3.806450
  train accuracy:                55.59 %
  validation accuracy:                43.20 %
Epoch 19 of 30 took 4.179s
  training loss (in-iteration):                3.757564
  train accuracy:                57.03 %
  validation accuracy:                43.20 %
Epoch 20 of 30 took 4.165s
  training loss (in-iteration):                3.713492
  train accuracy:                58.41 %
  validation accuracy:                42.40 %
Epoch 21 of 30 took 4.181s
  training loss (in-iteration):                3.673273
  train accuracy:                59.66 %
  validation accuracy:                42.20 %
Epoch 22 of 30 took 4.169s
  training loss (in-iteration):                3.635788
  train accuracy:                60.59 %
  validation accuracy:                43.00 %
Epoch 23 of 30 took 4.188s
  training loss (in-iteration):                3.601693
  train accuracy:                61.66 %
  validation accuracy:                40.60 %
Epoch 24 of 30 took 4.169s
  training loss (in-iteration):                3.569888
  train accuracy:                63.17 %
  validation accuracy:                41.60 %
Epoch 25 of 30 took 4.192s
  training loss (in-iteration):                3.539712
  train accuracy:                63.79 %
  validation accuracy:                41.00 %
Epoch 26 of 30 took 4.172s
  training loss (in-iteration):                3.510056
  train accuracy:                64.86 %
  validation accuracy:                41.40 %
Epoch 27 of 30 took 4.164s
  training loss (in-iteration):                3.482480
  train accuracy:                66.41 %
  validation accuracy:                40.20 %
Epoch 28 of 30 took 4.187s
  training loss (in-iteration):                3.455721
  train accuracy:                67.69 %
  validation accuracy:                40.80 %
Epoch 29 of 30 took 4.164s
  training loss (in-iteration):                3.428972
  train accuracy:                68.83 %
  validation accuracy:                41.20 %
Epoch 30 of 30 took 4.173s
  training loss (in-iteration):                3.419649
  train accuracy:                68.41 %
  validation accuracy:                41.20 %
```

7 Results

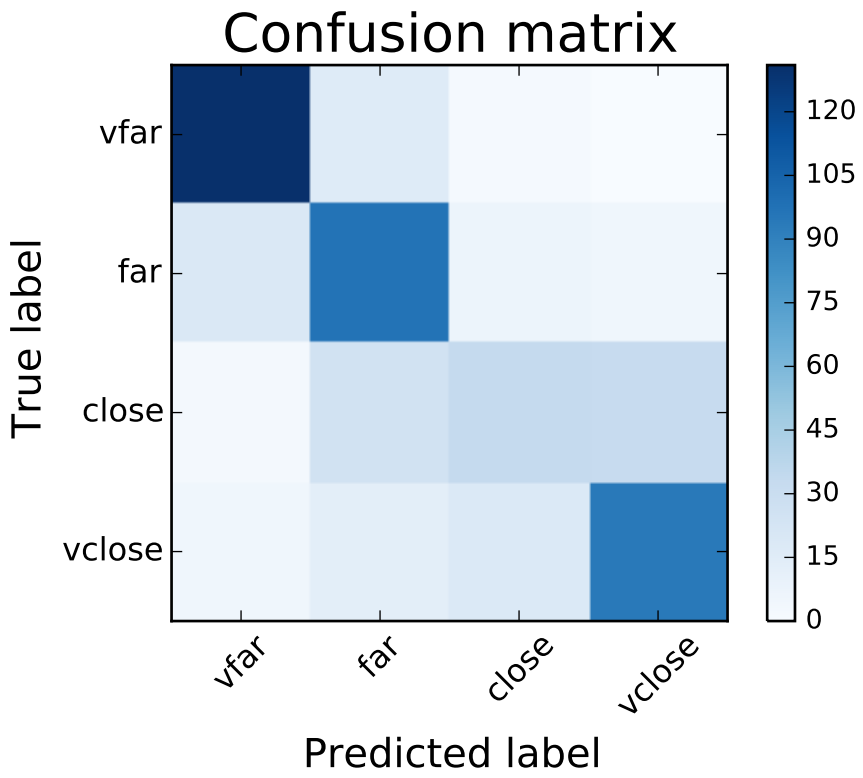
The best score was achieved with stacking technique.

In [23]:
```
from stacking import Stacking

        basic_wildfowl = Stacking(base_estimators=[
                (LogisticRegression(C=0.01, penalty='l1').fit,
                 lambda clf, X: clf.predict(X)),
                (lambda X, y: LinearSVC(C=1, penalty='l2', loss='squared_hinge',
                                        dual=True, multi_class='crammer_singer').fit(normalizer.transfo
                 lambda clf, X: clf.predict(normalizer.transform(X))),
                (lambda X, y: LogisticRegression(C=8, penalty='l1').fit(normalizer.transform(X), y),
                 lambda clf, X: clf.predict(normalizer.transform(X))),
                (lambda X, y: SVC(C=1, kernel='rbf', gamma=1).fit(normalizer.transform(X), y),
                 lambda clf, X: clf.predict(normalizer.transform(X))),
                (lambda X, y: SVC(C=1, kernel='poly', gamma=1, degree=2).fit(normalizer.transform(X), y
                 lambda clf, X: clf.predict(normalizer.transform(X)))],
                                    meta_fitter=SVC(C=1, kernel='rbf', gamma=0.2).fit,
                                    n_folds=5, extend_meta=False)
        y_predicted = basic_wildfowl.fit(np.array(f1_train), y_train).predict(np.array(f1_val))
```

```
/usr/lib64/python2.7/site-packages/sklearn/cross_validation.py:69: DeprecationWarning: The indices param
  stacklevel=1)
```

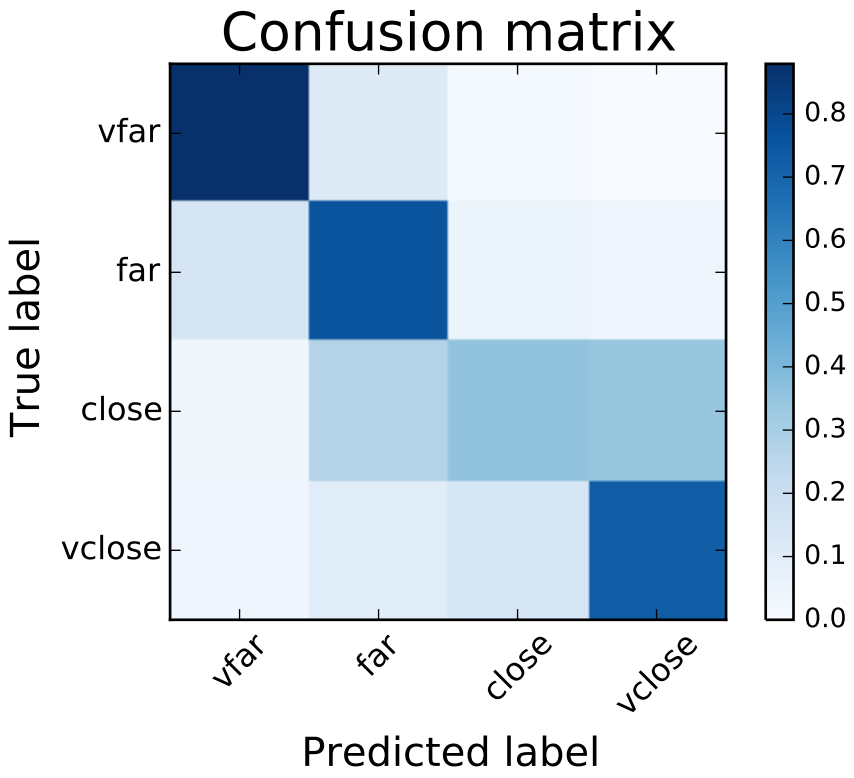
In [24]:
```
from sklearn.metrics import confusion_matrix

        def plot_confusion_matrix(cm, title='Confusion matrix', cmap=plt.cm.Blues):
            plt.figure(figsize=(5, 4))
            plt.imshow(cm, interpolation='nearest', cmap=cmap)
            plt.title(title, size=20)
            plt.colorbar()
            labels = ['vfar', 'far', 'close', 'vclose']
            tick_marks = np.arange(len(labels))
            plt.xticks(tick_marks, labels, rotation=45, size=12)
            plt.yticks(tick_marks, labels, size=12)
            plt.tight_layout()
            plt.ylabel('True label', size=15)
            plt.xlabel('Predicted label', size=15)
            plt.savefig('cm.pdf')
            plt.show()

        plot_confusion_matrix(confusion_matrix(y_val, y_predicted))
```

```
/usr/lib64/python2.7/site-packages/matplotlib/collections.py:590: FutureWarning: elementwise comparison
  if self._edgecolors == str('face'):
```




```
In [25]: A = confusion_matrix(y_val, y_predicted)
         np.set_printoptions(precision=2)
         print('Confusion matrix, without normalization')
         cm = A.astype(float) / A.sum(1, keepdims=True)
         print(cm)
         plt.figure()
         plot_confusion_matrix(cm)

Confusion matrix, without normalization
[[ 0.88  0.11  0.01  0.  ]
 [ 0.15  0.76  0.05  0.04]
 [ 0.03  0.27  0.35  0.34]
 [ 0.04  0.1   0.14  0.72]]

<matplotlib.figure.Figure at 0x18b410d0>
```

Segmentation	+		-	
Road	+	-	+	-
Neural Network	66.8%	NA	**67.7%**	66.7%
Logistic Regression	67.6%	66.6%	NA	**68.0%**
Normalization + LogReg	**67.7%**	NA	NA	67.0%
Linear SVC	67.6%	NA	NA	67.0%
PCA + SGB	58.8%	NA	59.7%	NA
Stacking of all above	NA %	NA	NA%	**70.6%**



Github: https://github.com/Avidereta/dl_project

8 Conclusion

While working on the project we:

- Accomplished Data Processing included segmentation (SegNet) and disparity map building (SGBM), noise reduction
- Developed and Experimented with Classifier based on features extracted from VGG19

From the confusion matrix it can be seen, that there are quite good results for the most interesting for us area (very close). Results:

9 Individual contribution

- Data preparation: Anastasia Makarova and others
- ML, Classifiers: Mikhail Karasikov
- External segmentation with SegNet and ANN training: Mikhail Usvyatsov
- All the other labor: All together