

Brilliantly wrong thoughts on science and programming

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Reconstructing pictures with machine learning [demonstration]

Feb 9, 2016 • Alex Rogozhnikov

Reconstructing pictures with machine learning [demonstration]

In this post I demonstrate how different techniques of machine learning are working.

The idea used is very simple:

- each black & white image can be treated as complex function of 2 variables - x and y, position of pixel
- intensity of pixel is output
- we can leave only small fraction of pixels, treating others as 'lost'
- by looking how different regression algorithms reconstruct picture, we can get some understanding of how those are operating

Don't treat this demonstration as some 'comparison of approaches', because this problem (reconstructing a picture) is very specific and has very few in common with typical ML datasets. And of course, this approach is not to be used in practice to reconstruct pictures :)

I am using scikit-learn and making use of its API, enabling user to construct new models via meta-ensembling and pipelines.

First, we import lots of things

```
[1]: # !pip install image
      from PIL import Image
      %pylab inline
```

Populating the interactive namespace from numpy and matplotlib

```
[2]: import numpy
from sklearn.pipeline import make_pipeline
from sklearn.ensemble import RandomForestRegressor, BaggingRegressor, Gra

from sklearn.cross_validation import train_test_split
from sklearn.random_projection import GaussianRandomProjection
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
from sklearn.kernel_approximation import RBFSampler
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor

from rep.metamodel import FoldingRegressor
from rep.estimators import XGBoostRegressor, TheanetsRegressor
```

◀ ▶

Download the picture ↴

I took quite complex picture with many little details

```
[3]: !wget http://orig05.deviantart.net/1d93/f/2009/084/5/2/new_york_black_and
```

◀ ▶

```
--2016-02-09 04:25:20-- http://orig05.deviantart.net/1d93/f/2009/084/5/2/
Resolving orig05.deviantart.net... 216.137.63.99, 216.137.63.108, 216.137
Connecting to orig05.deviantart.net|216.137.63.99|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 657820 (642K) [image/jpeg]
Saving to: 'image.jpg'
```

```
image.jpg          100%[=====] 642.40K 65.2KB/s in 1
```

```
2016-02-09 04:25:32 (60.0 KB/s) - 'image.jpg' saved [657820/657820]
```

◀ ▶

```
[4]: image = numpy.asarray(Image.open('./image.jpg')).mean(axis=2)
```

```
plt.figure(figsize=[20, 10])
plt.imshow(image, cmap='gray')
```

t[4]: <matplotlib.image.AxesImage at 0x10fc35690>



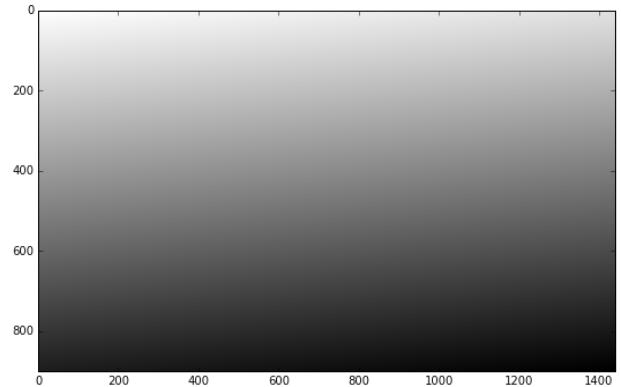
Define a function to train regressor

`train_size` is how many pixels shall be used in reconstructing the picture

```
[5]: def train_display(regressor, image, train_size=0.02):
    height, width = image.shape
    flat_image = image.reshape(-1)
    xs = numpy.arange(len(flat_image)) % width
    ys = numpy.arange(len(flat_image)) // width
    data = numpy.array([xs, ys]).T
    target = flat_image
    trainX, testX, trainY, testY = train_test_split(data, target, train_size)
    mean = trainY.mean()
    regressor.fit(trainX, trainY - mean)
    new_flat_picture = regressor.predict(data + mean)
    plt.figure(figsize=[20, 10])
    plt.subplot(121)
    plt.imshow(image, cmap='gray')
    plt.subplot(122)
    plt.imshow(new_flat_picture.reshape(height, width), cmap='gray')
```

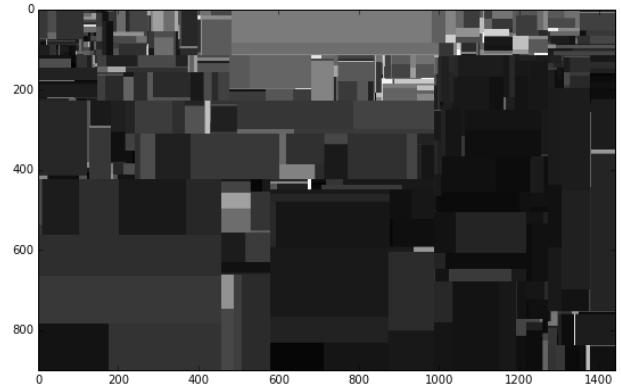
Linear regression ↴

```
[6]: train_display(LinearRegression(), image)
```



Decision tree limited by depth ↴

```
[7]: train_display(DecisionTreeRegressor(max_depth=10), image)
```

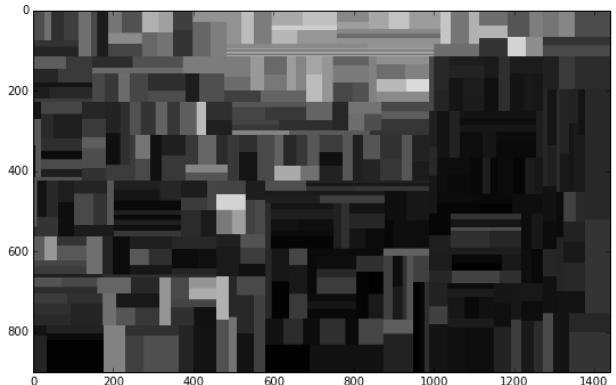


```
[8]: train_display(DecisionTreeRegressor(max_depth=20), image)
```

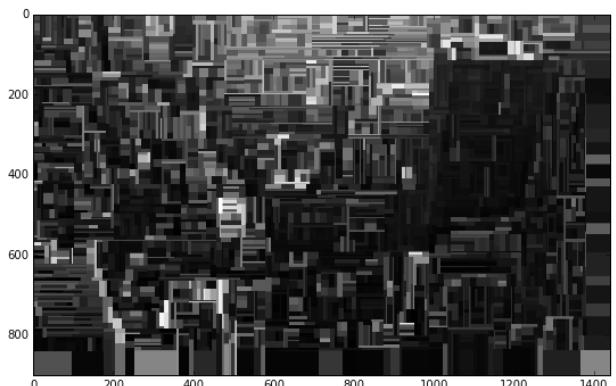


Decision tree limited by minimal number of samples in a leaf ↴

[9]: `train_display(DecisionTreeRegressor(min_samples_leaf=40), image)`



[10]: `train_display(DecisionTreeRegressor(min_samples_leaf=5), image)`



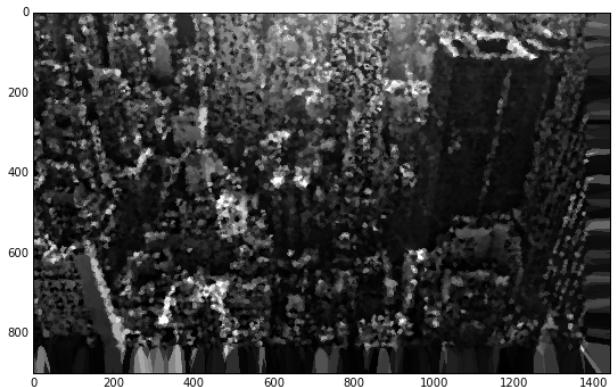
RandomForest

[11]: `train_display(RandomForestRegressor(n_estimators=100), image)`



K Nearest Neighbours

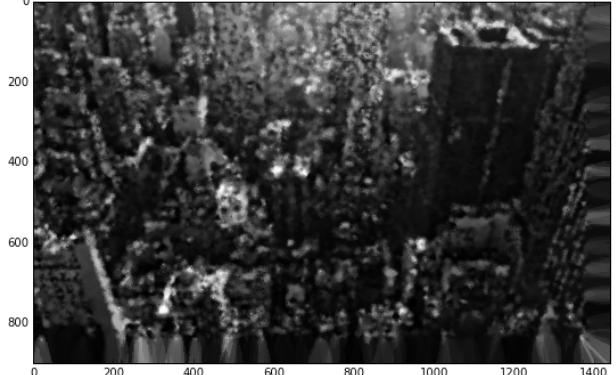
[12]: `train_display(KNeighborsRegressor(n_neighbors=2), image)`



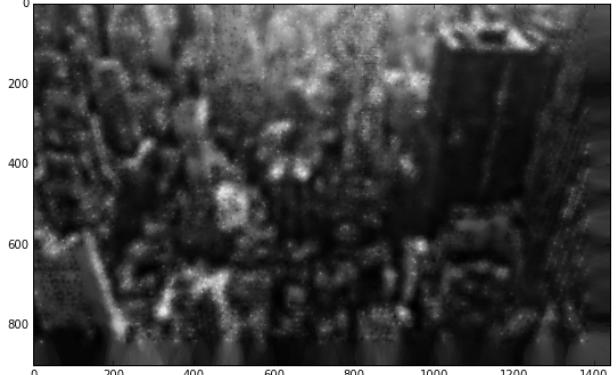
more neighbours + weighting according to distance

to make predictions smoother

13]: `train_display(KNeighborsRegressor(n_neighbors=5, weights='distance'), image)`

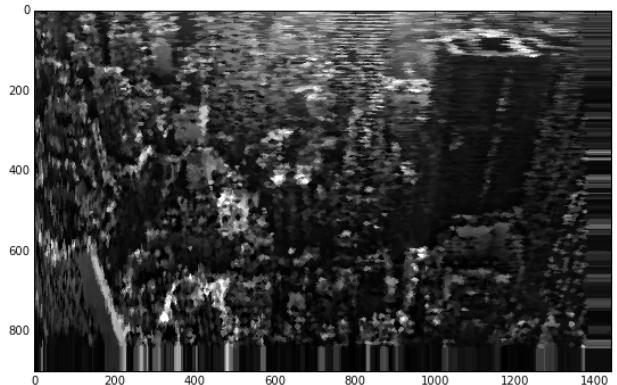


14]: `train_display(KNeighborsRegressor(n_neighbors=25, weights='distance'), image)`



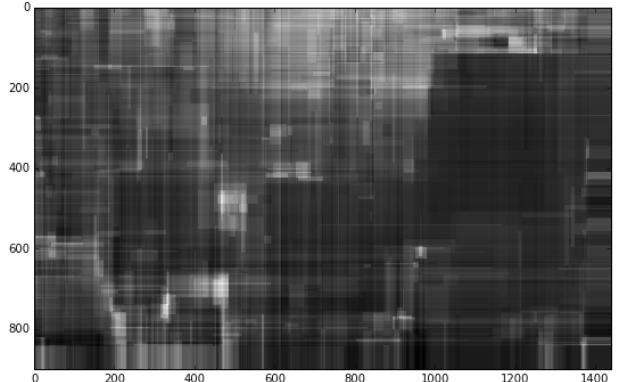
KNN with canberra metric

15]: `train_display(KNeighborsRegressor(n_neighbors=2, metric='canberra'), image)`



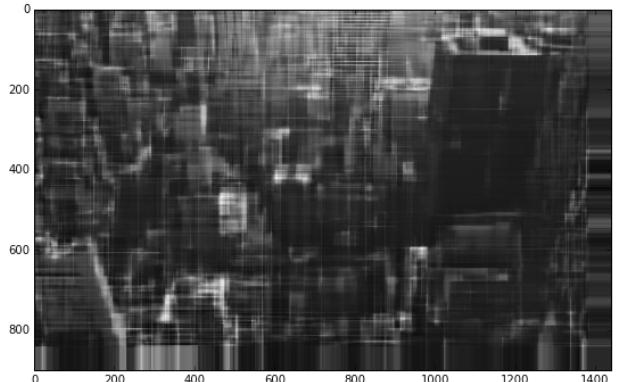
Gradient Boosting

```
16]: train_display(XGBoostRegressor(max_depth=5, n_estimators=100, subsample=0.5))
```



Gradient Boosting with deep trees

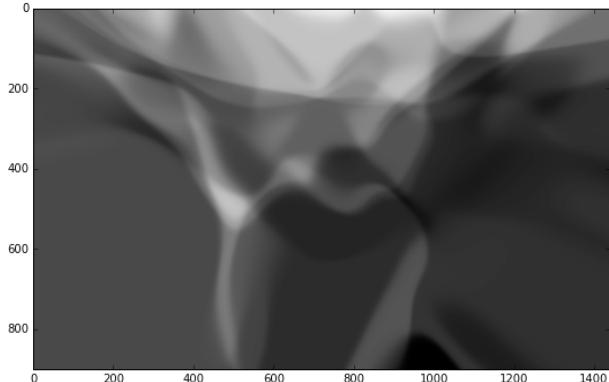
```
17]: train_display(XGBoostRegressor(max_depth=12, n_estimators=100, subsample=0.5))
```



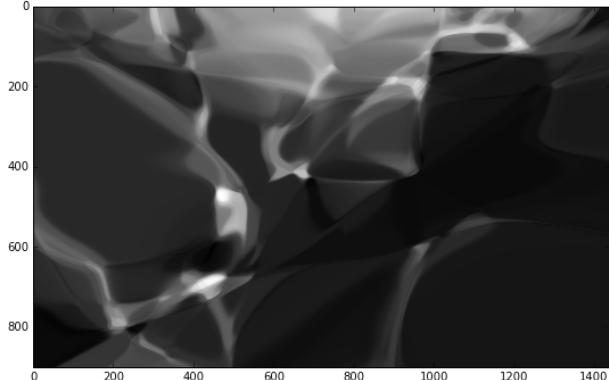
Neural networks

neural networks provide smooth predictions and are not able to deal with tiny sharp details of pictures.

```
18]: train_display(TheanetsRegressor(layers=[20, 20], hidden_activation='tanh'
                                         trainers=[{'algo': 'adadelta', 'learning_
```



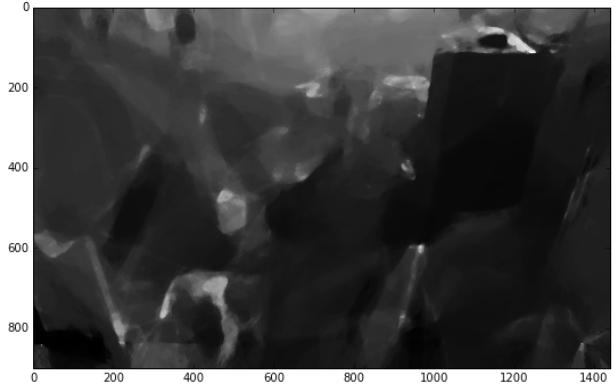
```
19]: train_display(TheanetsRegressor(layers=[40, 40, 40, 40], hidden_activation='tanh'
                                         trainers=[{'algo': 'adadelta', 'learning_
```



AdaBoost over Decision Trees using random projections

```
20]: base = make_pipeline(GaussianRandomProjection(n_components=10),
                         DecisionTreeRegressor(max_depth=10, max_features=5))
train_display(AdaBoostRegressor(base, n_estimators=50, learning_rate=0.05)
```

```
/Users/axelr/.conda/envs/rep/lib/python2.7/site-packages/sklearn/random_p
DataDimensionalityWarning)
```

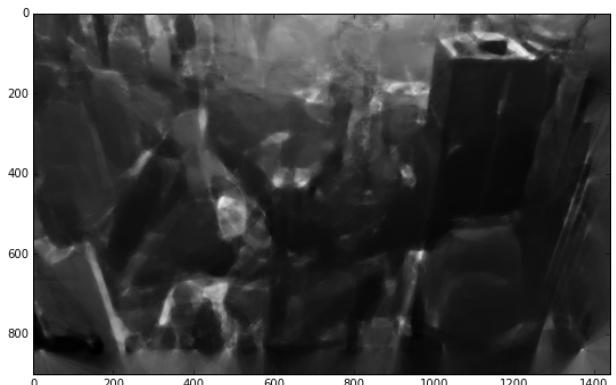


Bagging over decision trees using random projections

This is sometimes referred as Random Forest too (since this idea was proposed by Leo Breiman in the same paper).

```
21]: base = make_pipeline(GaussianRandomProjection(n_components=15),
                         DecisionTreeRegressor(max_depth=12, max_features=5))
train_display(BaggingRegressor(base, n_estimators=100), image)
```

```
/Users/axelr/.conda/envs/rep/lib/python2.7/site-packages/sklearn/random_
    DataDimensionalityWarning)
```



See also:

- Drawing an image with deep neural network Andrej Karpathy
- Artificial artist by Tim Head
- Painting photo in different artistic styles. Note that the study in this paper is quite different from things demonstrated in the post.

Feel free to download the notebook from repository and play with other images / parameters.

This post was written in IPython. You can download the notebook from [repository](#).

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