Problem 1

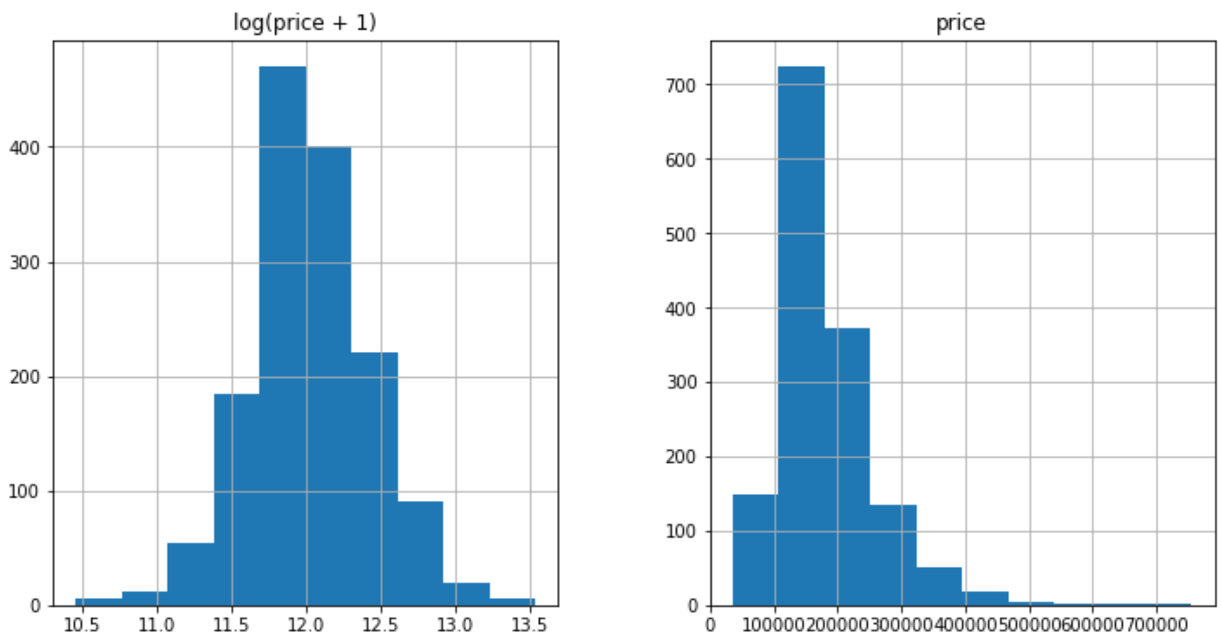
In [3]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib

import matplotlib.pyplot as plt
from scipy.stats import skew
from scipy.stats.stats import pearsonr


%config InlineBackend.figure_format = 'png' #set 'png' here when worki
ng on notebook
%matplotlib inline
```

In [4]:

```
# Preprocess Data for SKLearn

train = pd.read_csv("./input/train.csv")
test = pd.read_csv("./input/test.csv")

all_data = pd.concat((train.loc[:,'MSSubClass':'SaleCondition'],
                      test.loc[:,'MSSubClass':'SaleCondition']))

display(all_data.head())

matplotlib.rcParams['figure.figsize'] = (12.0, 6.0)
prices = pd.DataFrame({"price":train["SalePrice"], "log(price + 1)":np
.log1p(train["SalePrice"])})
prices.hist()

#log transform the target:
train["SalePrice"] = np.log1p(train["SalePrice"])

#log transform skewed numeric features:
numeric_feats = all_data.dtypes[all_data.dtypes != "object"].index

skewed_feats = train[numeric_feats].apply(lambda x: skew(x.dropna()))
#compute skewness
skewed_feats = skewed_feats[skewed_feats > 0.75]
skewed_feats = skewed_feats.index

all_data[skewed_feats] = np.log1p(all_data[skewed_feats])

all_data = pd.get_dummies(all_data)

#filling NA's with the mean of the column:
all_data = all_data.fillna(all_data.mean())

#creating matrices for sklearn:
X_train = all_data[:train.shape[0]]
X_test = all_data[train.shape[0]:]
y = train.SalePrice

def rmse_cv(model):
    rmse= np.sqrt(-cross_val_score(model, X_train, y, scoring="neg_mea
n_squared_error", cv = 5))
    return rmse
```

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilit
0	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllF
1	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllF
2	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllF
3	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllF
4	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllF

5 rows × 79 columns



In [70]:

```python
# Ridge Regression Model
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
from sklearn.linear_model import Ridge, RidgeCV, ElasticNet, Lasso, LassoCV, LassoLarsCV
from sklearn.model_selection import cross_val_score

def gen_csv(filename, model):
    preds = np.expm1(model.predict(X_test))
    df = pd.DataFrame({"Id": test["Id"], "SalePrice": preds})
    display(df.head())
    df.to_csv(filename, encoding='utf-8', index=False)
    return preds


model_ridge = Ridge(0.1)
model_ridge.fit(X_train, y)

print("RMSE Error for a=1: {0}".format(rmse_cv(model_ridge).mean()))

ridge_a1_preds = gen_csv("out/df_a1.csv", model_ridge)
```

```
RMSE Error for a=1: 0.1377753827718782
```

	Id	SalePrice
0	1461	121519.486569
1	1462	159637.898351
2	1463	187900.728019
3	1464	200719.158085
4	1465	199280.934855

In [71]:
```python
# Lasso Model

model_ridge_cv = RidgeCV(alphas = [1, 0.1, 0.001, 0.0005], cv = 5).fit
(X_train, y)
model_lasso_cv = LassoCV(alphas = [1, 0.1, 0.001, 0.0005], cv = 5).fit
(X_train, y)

print("RMSE for Ridge regression: {0}".format(rmse_cv(model_ridge_cv).
mean()))
print("RMSE for Lasso regression: {0}".format(rmse_cv(model_lasso_cv).
mean()))

ridge_preds = gen_csv("out/df_best_ridge.csv", model_ridge_cv)
lasso_preds = gen_csv("out/df_best_lasso.csv", model_lasso_cv)
```

```
RMSE for Ridge regression: 0.1313618498939958
RMSE for Lasso regression: 0.1225673588504815
```

	Id	SalePrice
0	1461	120420.655489
1	1462	153867.564298
2	1463	185515.001785
3	1464	199064.684452
4	1465	201164.850838

	Id	SalePrice
0	1461	119958.035681
1	1462	151482.567322
2	1463	180200.853648
3	1464	197515.619193
4	1465	202434.157491

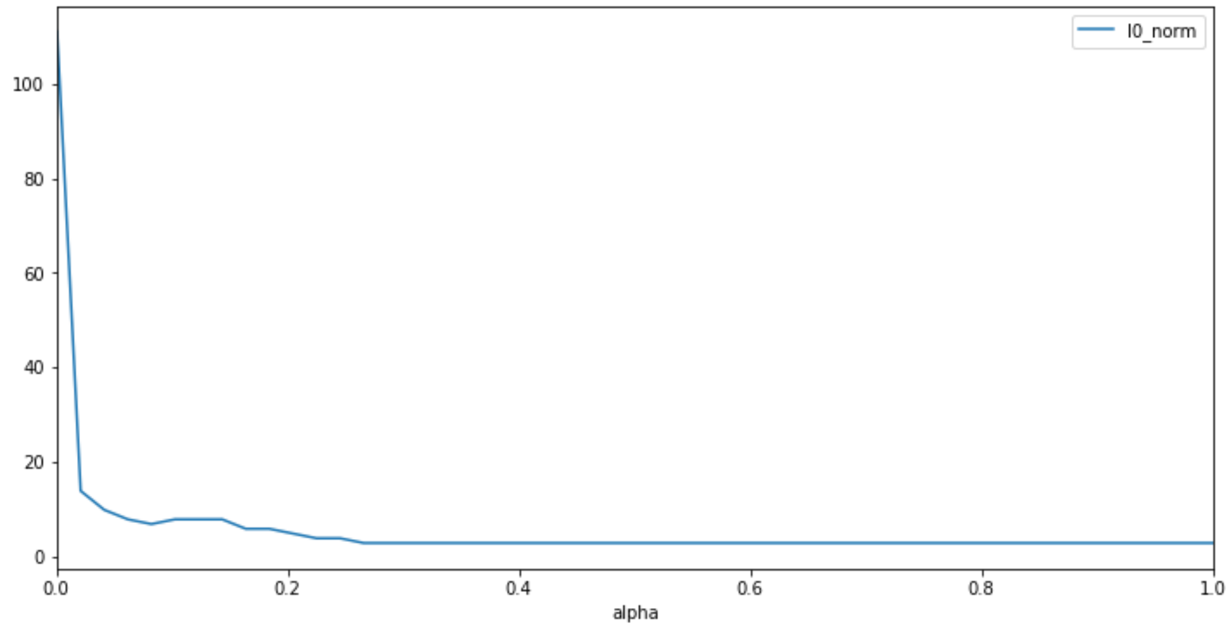
Kaggle Score for Best Ridge Regression

```
0.12661
```

Kaggle Score for Best Lasso Regression

```
0.12096
```

In [7]:
```
l0_norm = []

pnts = np.linspace(0.0005,1,50)
for alpha in pnts:
    m_r = Lasso(alpha).fit(X_train, y)
    l0_norm.append({"alpha": alpha, "l0_norm": sum(m_r.coef_ != 0)})

pd.DataFrame(l0_norm).set_index("alpha").plot()
plt.show()
```



In [111]:
```
# Ensembling
from mlxtend.regressor import StackingRegressor

X_ensemble_train = X_train.copy()
X_ensemble_train["ridge_prediction_1"] = model_ridge_cv.predict(X_trai
n)
X_ensemble_train["lasso_prediction_1"] = model_ridge_cv.predict(X_trai
n)

ridge_ensemble = RidgeCV(alphas = [2, 1, 0.1, 0.001, 0.0005], cv = 5).
fit(X_ensemble_train, y)

X_ensemble_test = X_test.copy()
X_ensemble_test["ridge_prediction_1"] = model_ridge_cv.predict(X_test)
X_ensemble_test["lasso_prediction_1"] = model_lasso_cv.predict(X_test)

ensemble_preds = np.expm1(ridge_ensemble.predict(X_ensemble_test))
ensemble_df = pd.DataFrame({"Id": test["Id"], "SalePrice": ensemble_pr
eds})

ensemble_df.to_csv("out/ensemble_df.csv", encoding='utf-8', index=Fals
e)

rmse = np.sqrt(-cross_val_score(ridge_ensemble, X_ensemble_train, y, s
coring="neg_mean_squared_error", cv = 5))
print("Ensemble Model RMSE: {0}".format(rmse.mean()))

display(ensemble_df.head())
```

```
Ensemble Model RMSE: 0.12193529667842676
```

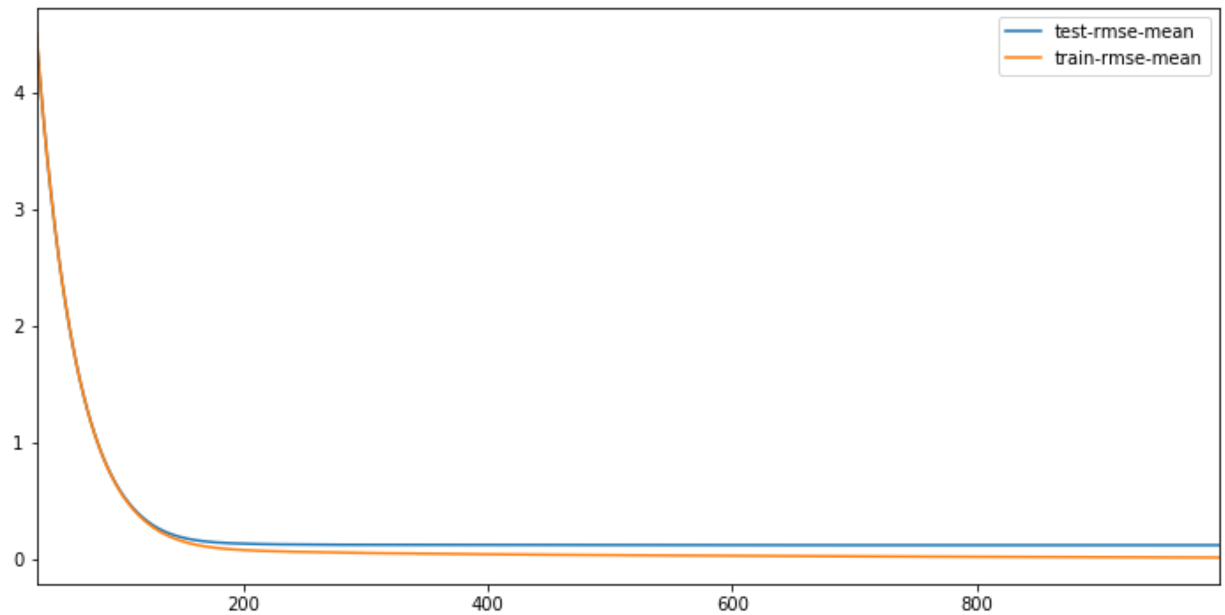
	Id	SalePrice
0	1461	120562.928600
1	1462	152865.778038
2	1463	183926.089607
3	1464	198646.918872
4	1465	201301.630835

Kaggle Score for Ensembling

```
0.12348
```

In [103]:
```
# XG BOOST
# First we need to tune parameters
import xgboost as xgb
from sklearn.model_selection import GridSearchCV, StratifiedKFold

dtrain = xgb.DMatrix(X_train, label = y)
dtest = xgb.DMatrix(X_test)

params = {'max_depth': 5, 'eta':0.03, 'silent':1, 'objective':'reg:linear', 'colsample_bytree': 0.3, 'alpha':0}

cv_results = xgb.cv(params, dtrain, num_boost_round=1000, early_stopping_rounds=300, metrics="rmse", as_pandas=True, seed=123)

cv_results.loc[30:,["test-rmse-mean", "train-rmse-mean"]].plot()
```

Out[103]: <matplotlib.axes._subplots.AxesSubplot at 0x11c8040f0>



In [104]:
```
model_xgb = xgb.XGBRegressor(n_estimators=600, learning_rate=0.03, max
_depth=5, objective ='reg:linear')
model_xgb.fit(X_train, y)

print("RMSE for XGB: {0}".format(rmse_cv(model_xgb).mean()))
xgb_preds = gen_csv("out/xgb_pred.csv", model_xgb)
```

```
RMSE for XGB: 0.12872432433086212
```

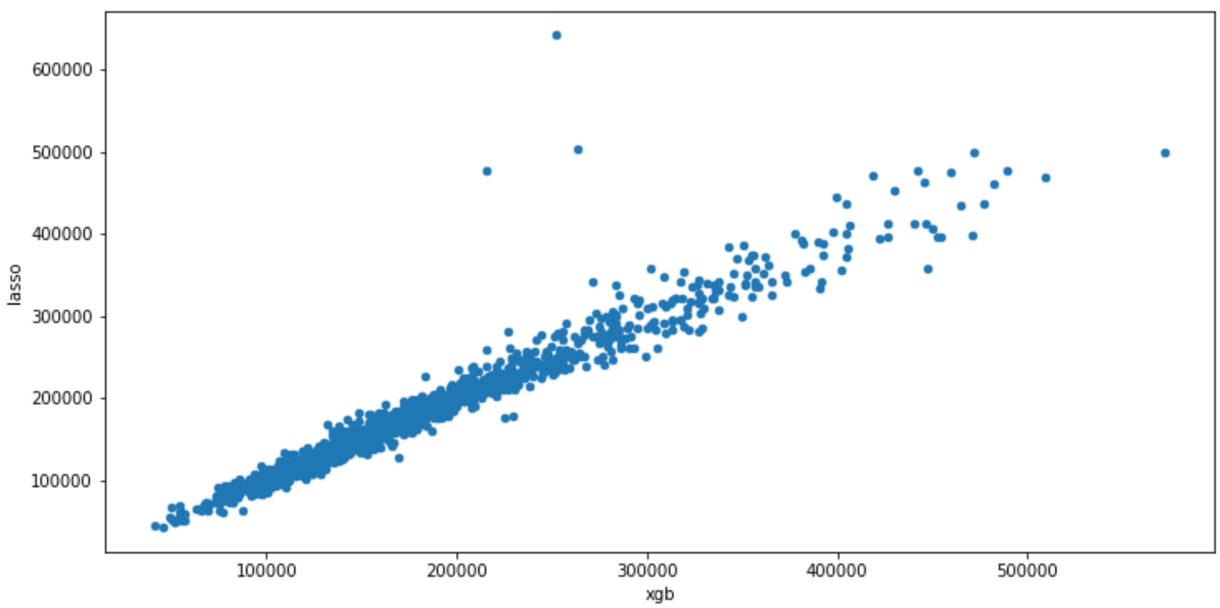
	Id	SalePrice
0	1461	121440.000000
1	1462	161743.687500
2	1463	186630.671875
3	1464	190171.953125
4	1465	184822.265625

Kaggle score for XG Boost

0.13414

In [99]:
```
predictions = pd.DataFrame({"xgb":xgb_preds, "lasso":lasso_preds})
predictions.plot(x = "xgb", y = "lasso", kind = "scatter")
```

Out[99]: <matplotlib.axes._subplots.AxesSubplot at 0x1297a7d68>



In [ ]:

```
#Trying for best model
# Stack Lasso with XGB
from mlxtend.regressor import StackingCVRegressor

meta_model = LassoCV(alphas = [1, 0.1, 0.001, 0.0005], cv = 5)

stacked = StackingRegressor(regressors=[model_xgb, model_lasso_cv],
                            meta_regressor=meta_model)

stacked.fit(X_train, y)
print("RMSE for Stacked: {0}".format(rmse_cv(stacked).mean()))
stacked_preds = gen_csv("out/stacked_pred.csv", model_xgb)
```

Kaggle Score for Stacked

```
0.13624
```

While this seemed like a good idea in practice, the Kaggle Score is lower than just using the Lasso Model. To get a better result, we could explore different types meta models for training on the aggregated data.

In [107]:

```
# Alternate approach, average lasso and xgb predictions

best_df = pd.DataFrame({"Id": test["Id"], "SalePrice": 0.7*lasso_preds
+ 0.3*xgb_preds})

best_df.to_csv("out/df_best.csv", encoding='utf-8', index=False)
```

Kaggle Score for Averaging

```
0.12021
```

This was the best score we were able to get. We fine-tuned XBG to not overfit the data and then averaged the results with Lasso's predictions. In the plot of XGB predictions vs Lasso Predictions, we can see that there are some data points where the output of Lasso is wildly different from XGB, and by averaging the output from both models we are likely reducing those errors.

Forum Reflection

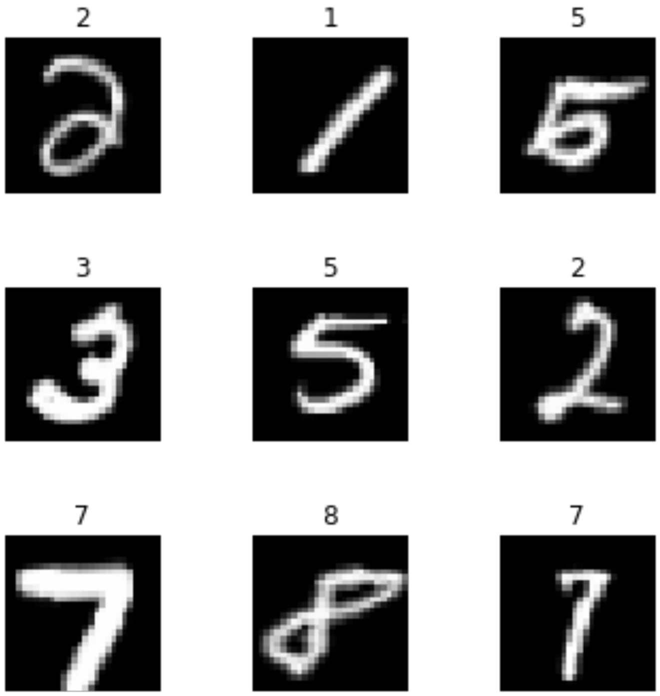
We looked on the forum for inspiration when looking for the best method to perform our regression. One that particularly stood out was a post by user MeiChengShih that detailed his stacking of 15 different models to optimize his result, and he showed that it significantly increased his score. Looking forward to our final project and Kaggle competition, we will definitely consider such comprehensive stacking in our methodology. He also detailed his use of outlier detection to improve his model. He did this by finding a set of outliers to remove from his training set. He then retrained his model using this new set and got a significantly better result. Had the scope of this lab been greater, we may have implemented something like this. Another example of this can be found in a post by user Andy Harless in which he exemplifies the importance of taking simple, logarithmic averages in order to improve your score. Finally, we were surprised in general at the wealth of knowledge contained in the posts. Many people openly shared their thinking in regards to the competition, and in reading through them we were given a more realistic look at possible ways that we could take our future tasks.

Problem 2

In [7]:
```
%reload_ext autoreload
%autoreload 2
%matplotlib inline

from fastai.vision import *
from fastai.metrics import error_rate
import pandas as pd
```

In [52]:
```
# learn = create_cnn(data, models.resnet34, metrics=error_rate)
help(create_cnn)

path=untar_data(URLs.MNIST)
```

In [55]:
```
data = ImageDataBunch.from_folder(path, train="training", valid="testing", ds_tfms=get_transforms(do_flip=False), size=28)
data.show_batch(rows=3, figsize=(5,5))
```

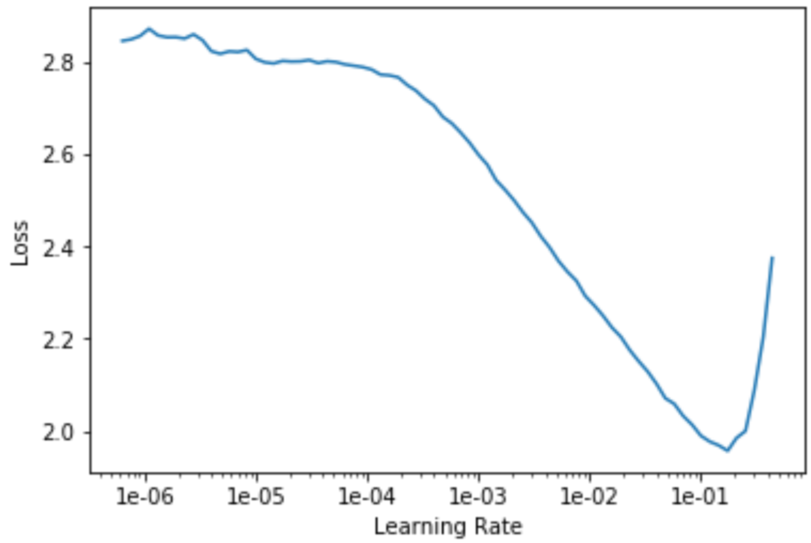


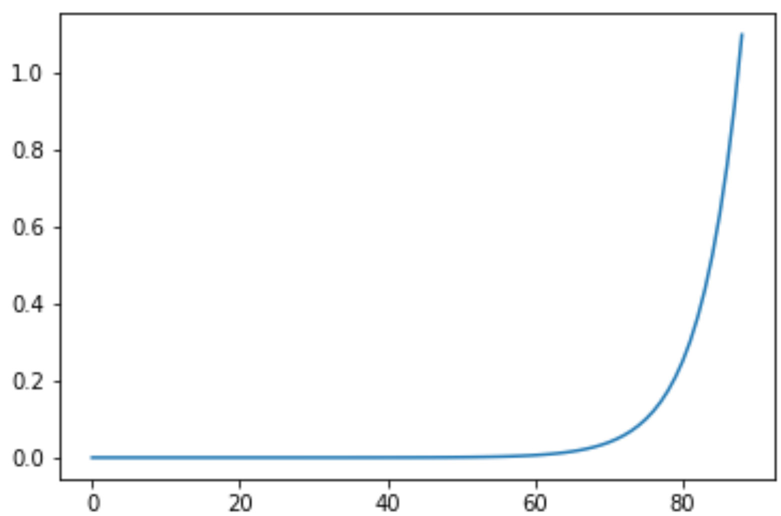
In [76]:
```
learn = create_cnn(data, models.resnet34, metrics=error_rate, pretrained=False)
```

In [77]:
```
learn.lr_find()
```

```
LR Finder is complete, type {learner_name}.recorder.plot() to see the graph.
```

In [78]:
```
learn.recorder.plot()

plt.figure()
learn.recorder.plot_lr()
```





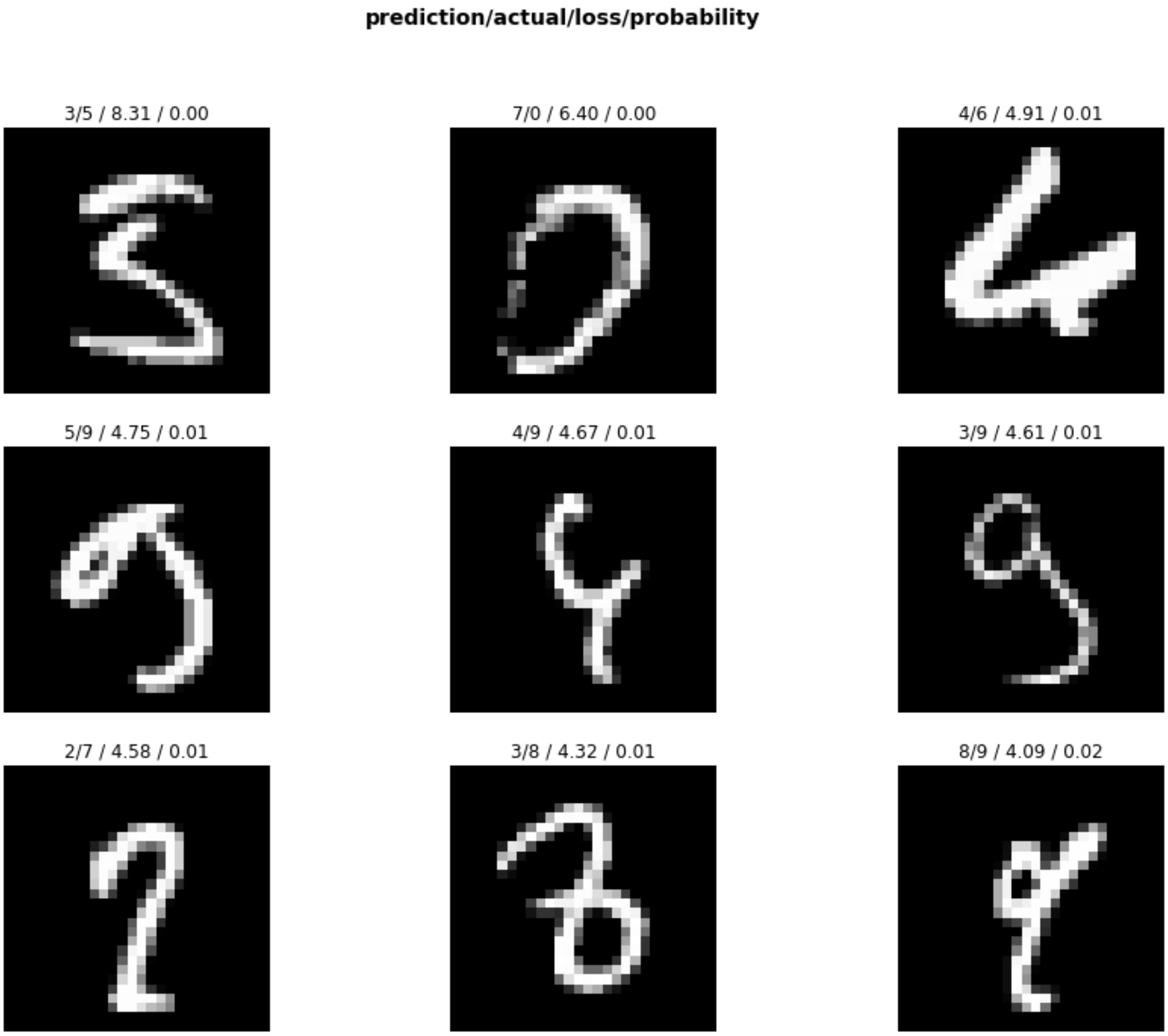
In [80]:
```
learn.fit_one_cycle(4)
```

Total time: 03:03

epoch	train_loss	valid_loss	error_rate
1	0.263670	0.155051	0.044000
2	0.119142	0.084666	0.023100
3	0.061374	0.027216	0.008600
4	0.037989	0.019857	0.006200

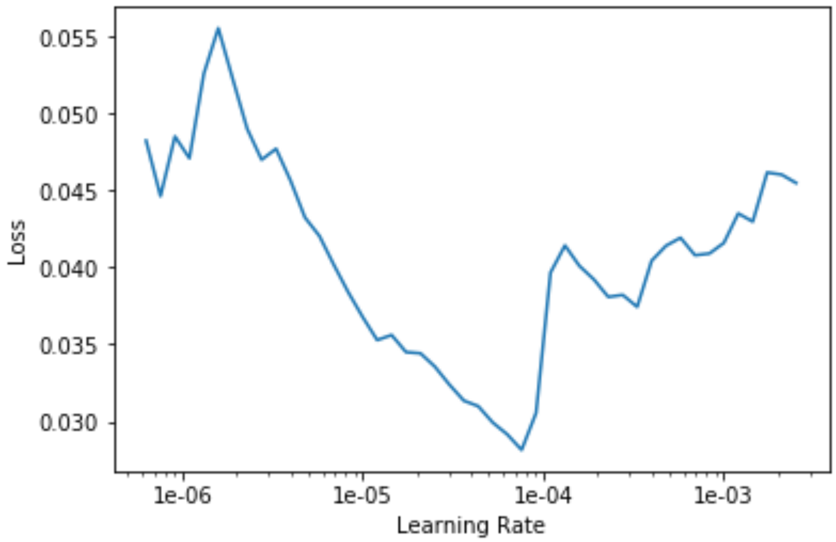
In [81]:
```
learn.save('stage-1')
```

In [82]:
```
interp = ClassificationInterpretation.from_learner(learn)

losses,idxs = interp.top_losses()

interp.plot_top_losses(9, figsize=(15,11))
```



In [83]:
```
learn.unfreeze()
learn.fit_one_cycle(1)
learn.load('stage-1')
learn.lr_find()
learn.recorder.plot()
```

```
LR Finder is complete, type {learner_name}.recorder.plot() to see th
e graph.
```



In [84]:
```
# Final time fit based on learning rate slice

learn.unfreeze()
learn.fit_one_cycle(2, max_lr=slice(1e-5,1e-4))
```

Total time: 01:29

epoch	train_loss	valid_loss	error_rate
1	0.033732	0.021069	0.005600
2	0.024694	0.019311	0.006100