SCHOOL OF DATA AND COMPUTER SCIENCE, SUN YAT-SEN UNIVERSITY

E14 BP Algorithm (C++/Python)

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December 14, 2019

Contents

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from nn import NN
from utilities import load_data, placeholder, Scaler, Accuracy, GridSearch,␣
↪plot_costs_epoch

%matplotlib inline
```

1 Pre-processing

1.1 Load Data

[2]:
```
train_data = load_data('./horse-colic.data', sep=' ')
test_data = load_data('./horse-colic.test', sep=' ')

# Combine for convenience
concat_index = len(train_data)
train_data = pd.concat([train_data, test_data], axis=0)
train_data.reset_index(drop=True, inplace=True)
display(train_data)
```

```
    surgery  Age  Hospital_Num rectal_temp pulse respiratory_rate extremities  \
0         2    1        530101       38.50    66               28           3
1         1    1        534817        39.2    88               20           ?
2         2    1        530334       38.30    40               24           1
3         1    9       5290409       39.10   164               84           4
4         2    1        530255       37.30   104               35           ?
..      ...  ...           ...         ...   ...              ...         ...
363       2    1        529695       38.60    60               30           1
364       2    1        528452       37.80    42               40           1
365       1    1        534783          38    60               12           1
366       2    1        528926       38.00    42               12           3
367       2    1        530670       37.60    88               36           3

[368 rows x 29 columns]
```

1.2 Simple Cleaning

1. Drop the last 2 columns, and hosipital num:
   - one of extra spaces
   - another is sure to be useless according to .name file.
2. Replace '?' with nan, and check how many missing values there are.
3. Split lesions.
4. Place the label(column 23) at last.
5. Transfer data type with to_numeric() (int or float).
6. Age '9' to '0', Surgery '2' to '0'.

[3]:
```
# 1
train_data.drop(train_data.columns[-2:], 1, inplace=True)
train_data.drop('Hospital_Num', 1, inplace=True)
```

[4]:
```
# 2
train_data.replace('?', np.nan, inplace=True)
```

[5]:
```
# 3
lesions = [train_data['lesion_1'], train_data['lesion_2'],␣
 ↪train_data['lesion_3']]
print(pd.unique(train_data['lesion_3']))
# lesion_3 is of almost no use in common
train_data.drop('lesion_3', 1, inplace=True)
```

```
[   0 2209]
```

[6]:
```
lesions1 = [str(i) for i in lesions[0]]
for idx, i in enumerate(lesions1):
    if len(i) == 4:
        lesions1[idx] = '0' + lesions1[idx]
    elif len(i) == 5:
        if i[:2] == '11' and i[-2:] == '10':
            lesions1[idx] = '0' + lesions1[idx]
        elif i[:2] != '11' and i[-2:] == '10':
            lesions1[idx] = '0' + lesions1[idx]
    else:
        lesions1[idx] = '0'*(5-len(i)) + lesions1[idx]
site1, type1 = pd.Series([i[:2] for i in lesions1], name='site1'), pd.
 ↪Series([i[2] for i in lesions1], name='type1')
stype1, scode1 = pd.Series([i[3] for i in lesions1], name='stype1'), pd.
 ↪Series([i[4:] for i in lesions1], name='scode1')

train_data.drop('lesion_1', 1, inplace=True)
train_data = pd.concat([train_data, site1, type1, stype1, scode1], axis=1)
```

[7]:
```python
lesions2 = [str(i) for i in lesions[0]]
for idx, i in enumerate(lesions2):
    if len(i) == 4:
        lesions2[idx] = '0' + lesions2[idx]
    elif len(i) == 5:
        if i[:2] == '11' and i[-2:] == '10':
            lesions1[idx] = '0' + lesions2[idx]
        elif i[:2] != '11' and i[-2:] == '10':
            lesions2[idx] = '0' + lesions2[idx]
    else:
        lesions2[idx] = '0'*(5-len(i)) + lesions2[idx]
site2, type2 = pd.Series([i[:2] for i in lesions2], name='site2'), pd.
 ↪Series([i[2] for i in lesions2], name='type2')
stype2, scode2 = pd.Series([i[3] for i in lesions2], name='stype2'), pd.
 ↪Series([i[4:] for i in lesions2], name='scode2')

train_data.drop('lesion_2', 1, inplace=True)
train_data = pd.concat([train_data, site2, type2, stype2, scode2], axis=1)
```

[8]:
```python
# 4
label = train_data['outcome']
train_data = train_data.drop(['outcome'], axis=1)
train_data = pd.concat([train_data, label], axis=1)
```

[9]:
```python
# 5
for i in train_data.columns:
    train_data[i] = train_data[i].map(np.float64)
```

[10]:
```python
# 6
train_data['surgery'] = train_data['surgery'].map({1:1, 2:0})
train_data['Age'] = train_data['Age'].map({1:1, 9:0})
```

From these results, we found many missing value even mostly up to 247 missing in 300.

However, the dataset has only 300 samples which make each of them crucial.

That is to say, there's a long way to go to fix it!(instead of merely drop the sample…)

2 Feature Engineering

Fortunately, from the .name file we can retrieve much help from the description on attributes.

2.1 Missing Rate

Calculate the missing rate of each feature, if the rate goes beyond 60%, discard the feature.

[11]:
```
missing_rate = {}
for i in train_data.columns:
    missing_rate[i] = 100 * list(train_data[i].isna()).count(True) /␣
 ↪len(train_data)

for k in missing_rate:
    if missing_rate[k] > 60:
        print(k)
        train_data.drop(k, 1, inplace=True)
```

```
nasogastric_reflux_PH
abdomcentesis_total_protein
```

2.2 Seperate Continuous/Categorical/UnorderedCategorical(Nominal) Features

[12]:
```
vals_list = [len(pd.unique(train_data[i])) for i in train_data]
print(vals_list)
```

```
[3, 2, 41, 55, 41, 5, 5, 7, 4, 6, 5, 5, 4, 4, 5, 6, 55, 85, 4, 2, 12, 5, 4, 11,
12, 5, 4, 11, 4]
```

[13]:
```
Continuous = ['rectal_temp', 'pulse', 'respiratory_rate', 'packed_cell_volume',␣
 ↪'total_protein']
Categorical = ['Age', 'extremities', 'peripheral_pulse','capillary_refill-time',
               'peristalsis', 'nasogastric_reflux', 'feces']
Nominal = ['surgery', 'pain', 'mucous_membranes', 'abdominal_distension',␣
 ↪'nasogastric_tube',
           'abdomen', 'abdominocentesis_appearance', 'surgical_lesion', 'site1',␣
 ↪'type1',
           'stype1', 'scode1', 'site2', 'type2', 'stype2', 'scode2']
```

2.3 Fix features

- For Continuous NaN value, Fill with mean value.
- For Categorical NaN value, Fill with mode value.
- For Nominal NaN value, Fill with -1 value.

[14]:
```python
for i in train_data.columns:
    if i in Continuous:
        train_data[i].fillna(np.mean(train_data[i]), inplace=True)
    elif i in Categorical:
        train_data[i].fillna(train_data[i].mode()[0], inplace=True)
    else:
        train_data[i].fillna(-1, inplace=True)
```

[15]:
```python
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 368 entries, 0 to 367
Data columns (total 29 columns):
surgery                        368 non-null float64
Age                            368 non-null int64
rectal_temp                    368 non-null float64
pulse                          368 non-null float64
respiratory_rate               368 non-null float64
extremities                    368 non-null float64
peripheral_pulse               368 non-null float64
mucous_membranes               368 non-null float64
capillary_refill-time          368 non-null float64
pain                           368 non-null float64
peristalsis                    368 non-null float64
abdominal_distension           368 non-null float64
nasogastric_tube               368 non-null float64
nasogastric_reflux             368 non-null float64
feces                          368 non-null float64
abdomen                        368 non-null float64
packed_cell_volume             368 non-null float64
total_protein                  368 non-null float64
abdominocentesis_appearance    368 non-null float64
surgical_lesion                368 non-null float64
site1                          368 non-null float64
type1                          368 non-null float64
stype1                         368 non-null float64
scode1                         368 non-null float64
site2                          368 non-null float64
type2                          368 non-null float64
stype2                         368 non-null float64
scode2                         368 non-null float64
outcome                        368 non-null float64
```

```
dtypes: float64(28), int64(1)
memory usage: 83.5 KB
```

2.4 Fix sugery, outcome

[16]:
```
# sugery: Take the mode instead.
idx = train_data.surgery.loc[train_data.surgery==-1]
train_data.at[idx.index[0], 'surgery'] = train_data.surgery.mode()[0]
train_data.at[idx.index[1], 'surgery'] = train_data.surgery.mode()[0]
```

[17]:
```
# outcome: Unable to fix a label.
idx = train_data.outcome.loc[train_data.outcome==-1]
train_data.drop(index=idx.index, inplace=True)
```

2.5 One-hot Encoding on Nominal Features

[18]:
```
for i in Nominal:
    train_data = pd.concat([train_data.drop(i, 1), pd.get_dummies(train_data[i],␣
 ↪prefix=i)], 1)
```

2.6 StandardScalar

[19]:
```
scl = Scaler()
train_label = np.array(train_data['outcome'][0:concat_index-1])
test_label = np.array(train_data['outcome'][concat_index-1:])
train_data = scl.fit(train_data).transform(train_data)
```

3 Training Model

3.1 Split Data and Review

[20]:
```
# Training Data: Mind that a sample is removed from train_data because of the␣
↪lost of label
X_train = train_data[0:concat_index - 1, : -1].T
Y_train_1 = [1 if i==1 else 0 for i in train_label]
Y_train_2 = [1 if i==2 else 0 for i in train_label]
Y_train_3 = [1 if i==3 else 0 for i in train_label]
Y_train = np.array([Y_train_1, Y_train_2, Y_train_3])

# Testing Data
X_test = train_data[concat_index - 1:, : -1].T
Y_test_1 = [1 if i==1 else 0 for i in test_label]
Y_test_2 = [1 if i==2 else 0 for i in test_label]
Y_test_3 = [1 if i==3 else 0 for i in test_label]
Y_test = np.array([Y_test_1, Y_test_2, Y_test_3])

display(X_train[:10])
display(Y_train)
display(X_test[:10])
display(Y_test)
```

```
array([[ 0.2878198 ,  0.2878198 ,  0.2878198 , ...,  0.2878198 ,
         0.2878198 ,  0.2878198 ],
       [ 0.56816287,  1.65833642,  0.25668471, ..., -0.98922792,
        -2.5466187 , -1.45644515],
       [-0.17851584,  0.63372219, -1.13843352, ...,  0.04300362,
         1.07676111, -1.13843352],
       ...,
       [ 1.17895741,  1.17895741,  0.08655637, ...,  1.17895741,
         0.08655637,  0.08655637],
       [-0.54936243, -0.54936243, -0.54936243, ..., -0.54936243,
        -0.54936243, -0.54936243],
       [-0.17384884,  0.68599813, -1.89354277, ..., -0.17384884,
         0.68599813,  0.68599813]])
```

```
array([[0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1,
        1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0,
        ...,
        1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
        0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1]])
```

```
array([[ 2.87819799e-01,  2.87819799e-01,  2.87819799e-01,
         2.87819799e-01,  2.87819799e-01,  2.87819799e-01,
         2.87819799e-01,  2.87819799e-01,  2.87819799e-01,
```

```
        2.87819799e-01,  2.87819799e-01,  2.87819799e-01,
        ...,
       -1.73848840e-01, -1.89354277e+00,  6.85998127e-01,
       -1.73848840e-01, -1.89354277e+00,  6.85998127e-01,
        6.85998127e-01]])
```

```
array([[1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1,
        0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0,
        1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1,
        0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0,
        1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
        1],
       [0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
        0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0,
        0]])
```

[21]:

```python
print("Shape of X_train:", X_train.shape)
print("Shape of Y_train:", Y_train.shape)
print("Shape of X_test:", X_test.shape)
print("Shape of Y_test:", Y_test.shape)
```

```
Shape of X_train: (112, 299)
Shape of Y_train: (3, 299)
Shape of X_test: (112, 67)
Shape of Y_test: (3, 67)
```

3.2 GridSearching

GridSearch() is implemented in utilities.py, with a very simply strategy, go through all possible values of given attribute, return the best combination of them.

[22]:

```python
HIDDEN_DIMS = [4, 8, 10]
LRS = [0.01, 0.05, 0.1, 0.3, 0.5]
L2_LAMBD = [0.1, 0.3, 0.5]
OUTPUT_DIM = 3
input_dim, num_sample = X_train.shape

trainloader = placeholder(X_train, Y_train)
testloader = placeholder(X_test, Y_test)
```

[23]:

```python
best_params = GridSearch(10000, trainloader, testloader, num_sample, input_dim,␣
 ↪OUTPUT_DIM, HIDDEN_DIMS, LRS, L2_LAMBD)
```

```
GridSearching: Hidden_dim: 4, Learning Rate: 0.010000, L2 lambda: 0.100000 --->
Accuracy: 0.970149.
GridSearching: Hidden_dim: 4, Learning Rate: 0.010000, L2 lambda: 0.300000 --->
Accuracy: 0.910448.
GridSearching: Hidden_dim: 4, Learning Rate: 0.010000, L2 lambda: 0.500000 --->
Accuracy: 0.925373.
GridSearching: Hidden_dim: 4, Learning Rate: 0.050000, L2 lambda: 0.100000 --->
Accuracy: 0.955224.
GridSearching: Hidden_dim: 4, Learning Rate: 0.050000, L2 lambda: 0.300000 --->
Accuracy: 0.955224.
GridSearching: Hidden_dim: 4, Learning Rate: 0.050000, L2 lambda: 0.500000 --->
Accuracy: 0.910448.
GridSearching: Hidden_dim: 4, Learning Rate: 0.100000, L2 lambda: 0.100000 --->
Accuracy: 0.985075.
GridSearching: Hidden_dim: 4, Learning Rate: 0.100000, L2 lambda: 0.300000 --->
Accuracy: 0.985075.
GridSearching: Hidden_dim: 4, Learning Rate: 0.100000, L2 lambda: 0.500000 --->
Accuracy: 0.970149.
GridSearching: Hidden_dim: 4, Learning Rate: 0.300000, L2 lambda: 0.100000 --->
Accuracy: 0.970149.
GridSearching: Hidden_dim: 4, Learning Rate: 0.300000, L2 lambda: 0.300000 --->
Accuracy: 0.985075.
GridSearching: Hidden_dim: 4, Learning Rate: 0.300000, L2 lambda: 0.500000 --->
Accuracy: 0.985075.
GridSearching: Hidden_dim: 4, Learning Rate: 0.500000, L2 lambda: 0.100000 --->
Accuracy: 0.985075.
GridSearching: Hidden_dim: 4, Learning Rate: 0.500000, L2 lambda: 0.300000 --->
Accuracy: 0.985075.
GridSearching: Hidden_dim: 4, Learning Rate: 0.500000, L2 lambda: 0.500000 --->
Accuracy: 0.985075.
GridSearching: Hidden_dim: 8, Learning Rate: 0.010000, L2 lambda: 0.100000 --->
Accuracy: 0.955224.
GridSearching: Hidden_dim: 8, Learning Rate: 0.010000, L2 lambda: 0.300000 --->
Accuracy: 0.940299.
GridSearching: Hidden_dim: 8, Learning Rate: 0.010000, L2 lambda: 0.500000 --->
Accuracy: 0.955224.
GridSearching: Hidden_dim: 8, Learning Rate: 0.050000, L2 lambda: 0.100000 --->
Accuracy: 0.955224.
GridSearching: Hidden_dim: 8, Learning Rate: 0.050000, L2 lambda: 0.300000 --->
Accuracy: 0.910448.
GridSearching: Hidden_dim: 8, Learning Rate: 0.050000, L2 lambda: 0.500000 --->
Accuracy: 0.940299.
GridSearching: Hidden_dim: 8, Learning Rate: 0.100000, L2 lambda: 0.100000 --->
Accuracy: 0.925373.
GridSearching: Hidden_dim: 8, Learning Rate: 0.100000, L2 lambda: 0.300000 --->
Accuracy: 0.955224.
GridSearching: Hidden_dim: 8, Learning Rate: 0.100000, L2 lambda: 0.500000 --->
Accuracy: 0.985075.
```

```
GridSearching: Hidden_dim: 8, Learning Rate: 0.300000, L2 lambda: 0.100000 --->
Accuracy: 0.955224.
GridSearching: Hidden_dim: 8, Learning Rate: 0.300000, L2 lambda: 0.300000 --->
Accuracy: 0.985075.
GridSearching: Hidden_dim: 8, Learning Rate: 0.300000, L2 lambda: 0.500000 --->
Accuracy: 0.970149.
GridSearching: Hidden_dim: 8, Learning Rate: 0.500000, L2 lambda: 0.100000 --->
Accuracy: 0.940299.
GridSearching: Hidden_dim: 8, Learning Rate: 0.500000, L2 lambda: 0.300000 --->
Accuracy: 0.985075.
GridSearching: Hidden_dim: 8, Learning Rate: 0.500000, L2 lambda: 0.500000 --->
Accuracy: 0.985075.
GridSearching: Hidden_dim: 10, Learning Rate: 0.010000, L2 lambda: 0.100000 --->
Accuracy: 0.940299.
GridSearching: Hidden_dim: 10, Learning Rate: 0.010000, L2 lambda: 0.300000 --->
Accuracy: 0.940299.
GridSearching: Hidden_dim: 10, Learning Rate: 0.010000, L2 lambda: 0.500000 --->
Accuracy: 0.925373.
GridSearching: Hidden_dim: 10, Learning Rate: 0.050000, L2 lambda: 0.100000 --->
Accuracy: 0.925373.
GridSearching: Hidden_dim: 10, Learning Rate: 0.050000, L2 lambda: 0.300000 --->
Accuracy: 0.910448.
GridSearching: Hidden_dim: 10, Learning Rate: 0.050000, L2 lambda: 0.500000 --->
Accuracy: 0.970149.
GridSearching: Hidden_dim: 10, Learning Rate: 0.100000, L2 lambda: 0.100000 --->
Accuracy: 0.985075.
GridSearching: Hidden_dim: 10, Learning Rate: 0.100000, L2 lambda: 0.300000 --->
Accuracy: 0.970149.
GridSearching: Hidden_dim: 10, Learning Rate: 0.100000, L2 lambda: 0.500000 --->
Accuracy: 0.985075.
GridSearching: Hidden_dim: 10, Learning Rate: 0.300000, L2 lambda: 0.100000 --->
Accuracy: 0.970149.
GridSearching: Hidden_dim: 10, Learning Rate: 0.300000, L2 lambda: 0.300000 --->
Accuracy: 0.970149.
GridSearching: Hidden_dim: 10, Learning Rate: 0.300000, L2 lambda: 0.500000 --->
Accuracy: 0.985075.
GridSearching: Hidden_dim: 10, Learning Rate: 0.500000, L2 lambda: 0.100000 --->
Accuracy: 0.985075.
GridSearching: Hidden_dim: 10, Learning Rate: 0.500000, L2 lambda: 0.300000 --->
Accuracy: 0.955224.
GridSearching: Hidden_dim: 10, Learning Rate: 0.500000, L2 lambda: 0.500000 --->
Accuracy: 0.985075.
```

3.3 Store the best params

[24]:
```
# Store best_params
import os
import time
import pickle

path = './best_params.pk'
while os.path.exists(path):
    path = path[:-3] + '-' + '-'.join([str(i) for i in time.localtime()[:5]]) +␣
↪'.pk'
with open(path, 'wb') as pk:
    pickle.dump(best_params, pk)
```

3.4 Retrieve and Observation

[25]:
```
import pickle
with open('./best_params.pk', 'rb') as pk:
    best_params = pickle.load(pk)
```

[35]:
```
# Retrieve from best_params
hidden_dim = best_params['hidden_dim']
learning_rate = best_params['learning_rate']
params = best_params['params']
L2_lambd = best_params['L2_lambd']
costs = best_params['costs']
print("Best Parameters:")
print('- hidden dim:\t', hidden_dim)
print('- L2 lambd:\t', L2_lambd)
print('- learning rate:', learning_rate)
```

```
Best Parameters:
- hidden dim:    4
- L2 lambd:      0.1
- learning rate: 0.1
```

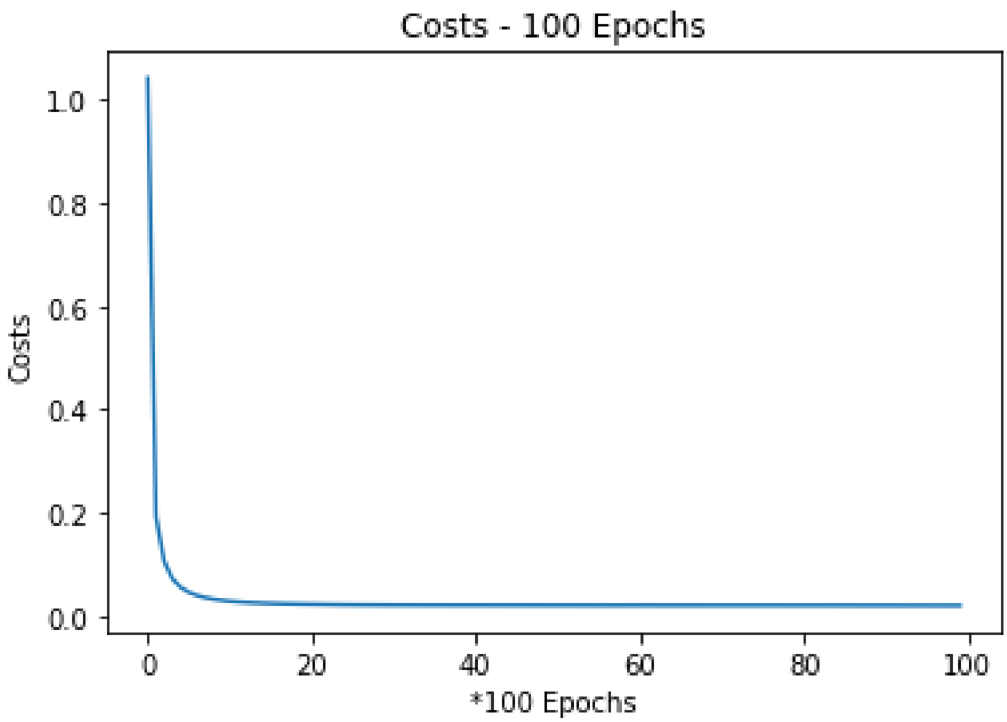
[27]:
```
# Build with best_params
clf = NN(num_sample, input_dim, hidden_dim, OUTPUT_DIM, init_method='He')
clf.params = params
```

[28]:
```
# Predicitons
train_predictions = clf.predict(X_train)
test_predictions = clf.predict(X_test)
print("Accuracy on Training set: {:.2f}%".format(100 *␣
↪Accuracy(train_predictions, Y_train)))
print("Accuracy on Training set: {:.2f}%".format(100 *␣
↪Accuracy(test_predictions, Y_test)))
```

```
Accuracy on Training set: 100.00%
Accuracy on Training set: 98.51%
```

[29]:
```
gaped_costs = costs[::100]
```

[30]:
```
plot_costs_epoch(gaped_costs)
```



4 Conclusion

As displayed above, the result of this model appears to be great.

To summarize my thoughts:

1. How to deal with 30% lost/missing data?

    - Firstly separate different types of features, that's because different type of features should be dealt with different methods;
    - For continuous data, mean value can only cause little displacement of feature distribution(naively thinking...);
    - For ordered Categorical data, mode value represents the common regularity of the feature;
    - For nominal data, filling with -1 means to add an extra possible value into the domain of the feature.

2. What to do with selecting hyperparameters?

    - Simulating and simplifying skleran-GridCVsearch, go through those posiibilities.

3. Model Structure?

```
# ================================================================
#   __m__         ___m____           __m___
#  |     |  W1   |        |   W2    |      |
# n|input| ---> h| hidden |  ---> y|output|
#  |     |       |        |         |      |
#   -----         --------           ------
# ----------------------------------------------------------------
# Accordingly:
#   - input: (n x m)
#   - W1:    (h x n)
#     W1 x input + bias = hidden  --> (h x n) x (n x m) -> (h x m)
#
#   - hidden:(h x m)
#   - W2:    (y x h)
#     W2 x hidden + bias = output --> (y x h) x (h x m) -> (y x m)
#
#   - output:(y x m)
# ----------------------------------------------------------------
# Params:
#   - W1:    (h x n)
#   - W2:    (y x h)
#   - bias1: (h x 1) (broadcast by numpy)
#   - bias2: (y x 1) (broadcast by numpy)
# ================================================================
```

For more, refer to module nn(nn.py)