Rademacher_F1

June 13, 2020

[768]:
```
import numpy as np
import matplotlib.pyplot as plt
import compute_parameters
import pandas as pd
import statsmodels.api as sm
from scipy.stats import norm
from scipy.optimize import curve_fit
import pylab
```

[769]:
```
def get_actual_predicted(trace, trace_name, jvm, hidden_size, history_size=40,
                         model_type="fcn", output_file_location="/media/arjun/
 ↪Shared/chaos/output_files"):
    start_point = 10000
    n_points = 5000

    if jvm == "jikes":
        jvm_name = "JikesRVM"
    elif jvm == "j9":
        jvm_name = "J9"
    else:
        jvm_name = "HotSpot"

    offset = 3

    data = []

    predictions = np.load(
                    '{}/{}/{}/predictions_{}_{}_{}_{}.npy'.
 ↪format(output_file_location,
                                                                    trace_name,␣
 ↪jvm, history_size,
                                                                    1,␣
 ↪hidden_size, 1))
    predictions = np.argsort(predictions)
#     print(predictions.shape)
#     print(trace.shape)
    for idx, point in enumerate(trace):
```

```
        if idx >= len(trace)-offset-1:
            continue
#         print("{}: {}".format(np.argmax(point),␣
 ↪predictions[history_size-1+idx, -1]))
        actual = bin_to_val(int(np.argmax(point)))
        predicted = bin_to_val(predictions[history_size+idx+offset, -1])

        data.append((actual, predicted))

    return data
```

[770]:
```
def mse_function(y, y1):
    return np.mean((y-y1)**2)

## precision and recall
def relevance_function(x, sigma=1.0, mu=0):
    return np.exp(-((x-mu)**2)/(2*(sigma**2)))/(sigma*np.sqrt(2*np.pi))


def relevance_function1(x, mu=0):
    return 1


def alpha(y, y_pred, loss_function=mse_function, threshold=3e-1):
    return loss_function(y, y_pred) < threshold


def recall(data, y_ref, loss_function=mse_function, relevance_threshold=0.3):
    num = 0
    din = 0
    for y_actual, y_pred in data:
        phi_y = relevance_function(y_actual, mu=y_ref)
        if phi_y >= relevance_threshold:
            num += alpha(y_actual, y_pred, loss_function) * phi_y
            din += phi_y

    if din > 0:
        return num/din
    else:
        return 0



def existance_check(data, y_ref, loss_function=mse_function,␣
 ↪relevance_threshold=0.3):
    num = 0
    din = 0
```

```
    exists = False
    for y_actual, y_pred in data:
        phi_y = relevance_function(y_actual, mu=y_ref)
        if phi_y >= relevance_threshold:
            return True

    return False


def precision(data, y_ref, loss_function=mse_function, relevance_threshold=0.3):
    num = 0
    din = 0
    for y_actual, y_pred in data:
        phi_y1 = relevance_function(y_pred, mu=y_ref)
        if phi_y1 >= relevance_threshold:
            num += alpha(y_actual, y_pred, loss_function) * phi_y1
            din += phi_y1

    if din > 0:
        return num/din
    else:
        return 0


def f1_score(precision, recall, beta=1):
    if precision+recall > 0:
        return ((1+beta**2)*precision*recall)/(precision+recall)
    else:
        return 0


def bin_to_val(bin_idx):
    g_max = 1
    g_min = 3 * np.exp(-8)
    feature_dimension = 100
    multiplier = (np.log(g_max) - np.log(g_min))/feature_dimension # values␣
 ↪from preprocess cache file

    return bin_idx*multiplier + np.log(g_min)
```

[771]:
```
def sup(arr, mode="max"):
    if mode == "max":
        return (np.max(arr))
    elif mode == "999percentile":
        return np.mean(arr) + 5 * np.std(arr)
```

```
def get_rademacher(loss_array):
    rademacher = []

    n_sigma = 2000

    for i in range(n_sigma):
        sigma_arr = np.random.choice([1, -1], size=loss_array.shape)

        f = sigma_arr*loss_array
        f = np.sum(f, axis=1)/loss_array.shape[1]
        # print(f)
        rademacher.append(sup(f))

    return np.mean(rademacher)
```

[772]:
```
def get_loss_dict1(trace, output_file_location, hidden_sizes=None,␣
↪trace_name="pmd", plot_graphs=False):

    if hidden_sizes is None:
        hidden_sizes = [ 10, 50, 100, 500, 1000, 2000, 3000, 4000, 5000, 6000,␣
↪7000, 8000 ]

    history_sizes = [ 5, 10, 15, 20, 25, 30, 35, 40, 45, 50 ]
    history_size = 40
    n_seeds = 30
    n_sets = 1
    n_points = 5000
    chunk_size = int(n_points/n_sets)
    relevance_threshold = relevance_function(1e-1)
    loss_dict = {}
    min_val = np.log(3e-8)
    max_val = 0
    n_steps = 50

    print("relevance threshold: {}".format(relevance_threshold))

    for hidden_size in hidden_sizes:
        loss_array = np.zeros((n_seeds, n_sets))
        print("hidden_size: {}".format(hidden_size))

        if hidden_size in loss_dict.keys():
            continue

        for seed in range(n_seeds):
            data1 = get_actual_predicted(trace, trace_name, "jikes",␣
↪hidden_size=hidden_size, history_size=40,
```

```
                        model_type="lstm",␣
↪output_file_location=output_file_location)

            indices = np.arange(0, n_points, chunk_size)

            for index in indices:
    #             print(index, index+chunk_size)
    #             print(np.linspace(0, n_points, n_sets))
                data = data1[index:index+chunk_size]
                recall_vals = []
                precision_vals = []
                f1_vals = []
                for val in np.linspace(min_val, max_val, n_steps):
                    recall_val = recall(data, val,␣
↪relevance_threshold=relevance_threshold)
                    precision_val = precision(data, val,␣
↪relevance_threshold=relevance_threshold)
                    recall_vals.append(recall_val)
                    precision_vals.append(precision_val)

#                     print("precision: {}, recall: {}".format(precision_val,␣
↪recall_val))
                    f1_vals.append(f1_score(precision_val, recall_val))

                f1_avg_list=[]
                for idx, val in enumerate(np.linspace(min_val, max_val,␣
↪n_steps)):
                    if existance_check(data, val,␣
↪relevance_threshold=relevance_threshold):
                        f1_avg_list.append(f1_vals[idx])

                if plot_graphs and index==0 and seed==1:
                    ax1=plt.subplot(1, 3, 1)
                    ax2=plt.subplot(1, 3, 2)
                    ax3=plt.subplot(1, 3, 3)

                    ax1.figure.set_size_inches(10, 3)
                    ax2.figure.set_size_inches(10, 3)
                    ax3.figure.set_size_inches(10, 3)

                    ax1.set_title("precision")
                    ax2.set_title("recall")
                    ax3.set_title("f1")

                    ax1.plot(np.linspace(min_val, max_val, n_steps),␣
↪precision_vals, label="precision")
```

```
                    ax2.plot(np.linspace(min_val, max_val, n_steps),␣
↪recall_vals, label="recall")
                    ax3.plot(np.linspace(min_val, max_val, n_steps), f1_vals,␣
↪label="f1")

                    ax1.set_ylim((-0.1, 1.1))
                    ax2.set_ylim((-0.1, 1.1))
                    ax3.set_ylim((-0.1, 1.1))

                    plt.title("Hidden: {}, seed: {}".format(hidden_size, seed))
                    plt.legend()
                    plt.show()

                chunk_idx = int(index/chunk_size)

                loss_array[seed, chunk_idx] = 1-np.average(f1_avg_list)
        loss_dict[hidden_size] = loss_array

    return loss_dict
```

[773]:
```
trace_name = "pmd"
start_point = 10000
n_points = 5000
jvm = "jikes"

if jvm == "jikes":
    jvm_name = "JikesRVM"
elif jvm == "j9":
    jvm_name = "J9"
else:
    jvm_name = "HotSpot"

trace = pd.read_pickle(
                '../data/{}-small-{}-d-l64-p4096-w100000i.analyzed-1.pkl'.
↪format(trace_name, jvm_name)
            ).to_numpy()[start_point:start_point+n_points]
```

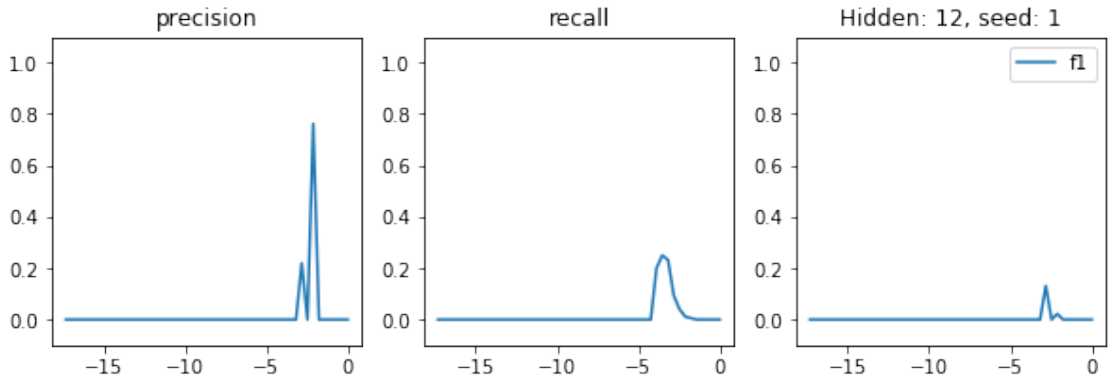
[774]:
```
loss_main = {}
# hidden_sizes=[ 1, 10, 100, 1000, 2000, 3000, 4000, 5000, 6000, 7000, 8000 ]
# hidden_sizes_lstm = [ 99, 148, 198, 248, 298, 347, 845, 1342,
#                       1840, 2337, 2835, 3332, 3830, 4327, 4825 ]

hidden_sizes_lstm = [ 10, 20, 30, 40, 50, 60, 70, 80, 90, 99, 148, 198, 248,␣
↪298, 347, 845, 1342,
                      1840, 2337, 2835, 3332, 3830, 4327, 4825 ]
hidden_sizes_fcn = [ 12, 14, 17, 19, 21, 24, 48, 73, 97, 121, 146, 170, 195,␣
↪219, 243 ]
```

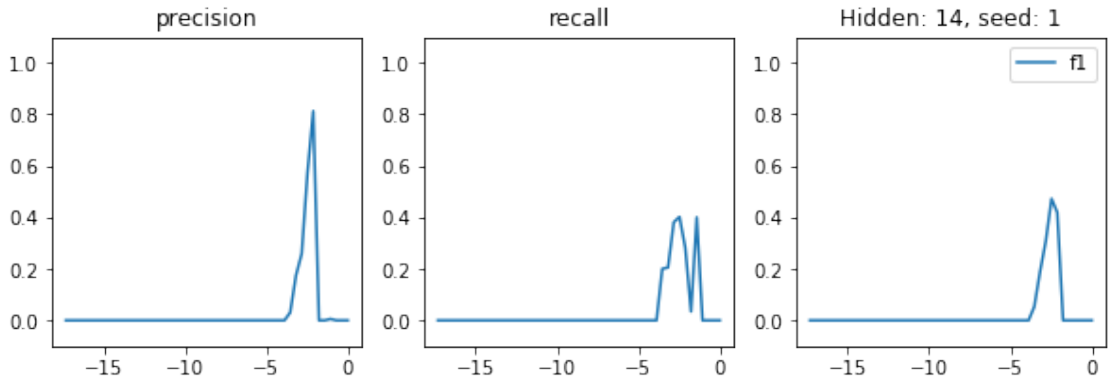
[775]:
```
hidden_sizes = hidden_sizes_fcn

loss_main["fcn"] = get_loss_dict1(trace, "/media/arjun/Shared/chaos/
 ↪output_files_v2/fcn",
                                   hidden_sizes=hidden_sizes, plot_graphs=True)
```

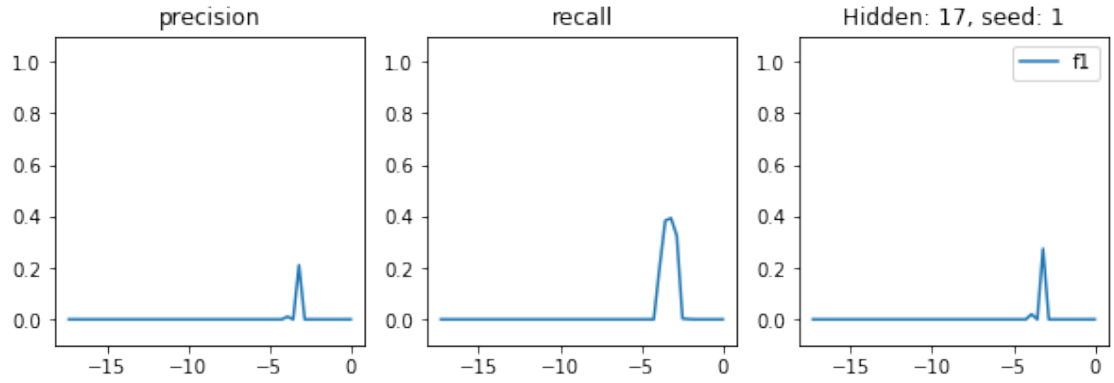
```
relevance threshold: 0.3969525474770118
hidden_size: 12
```



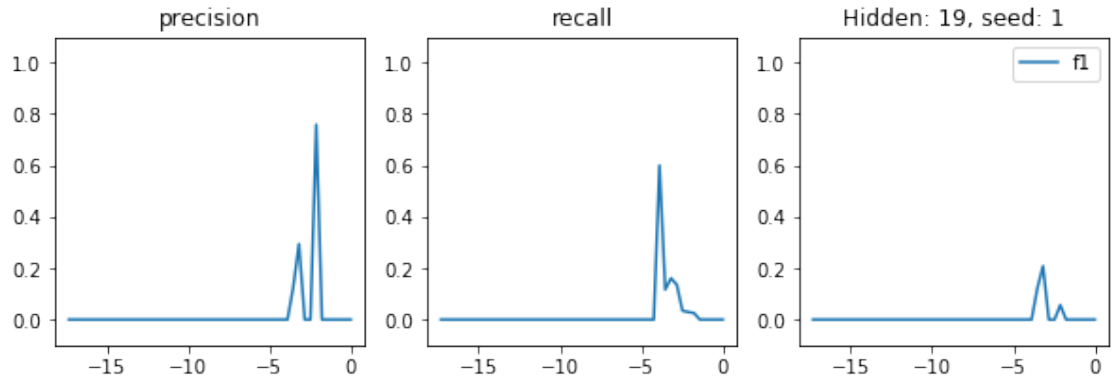

```
hidden_size: 14
```




```
hidden_size: 17
```



`hidden_size: 19`



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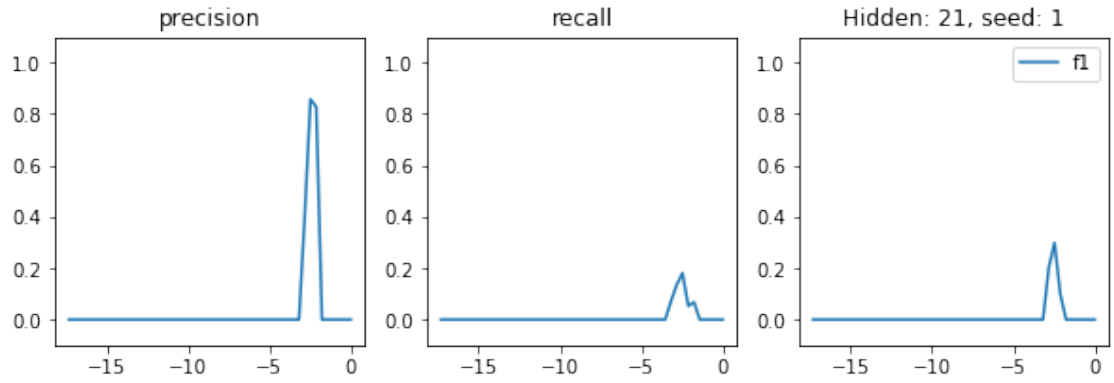

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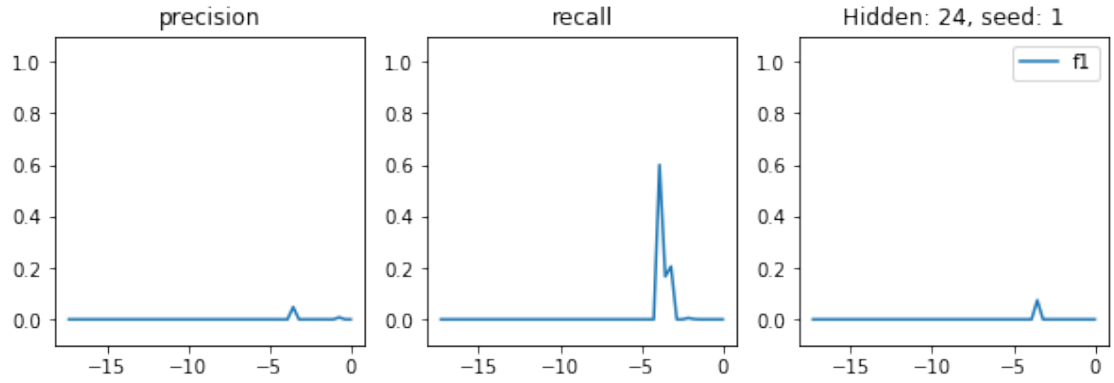

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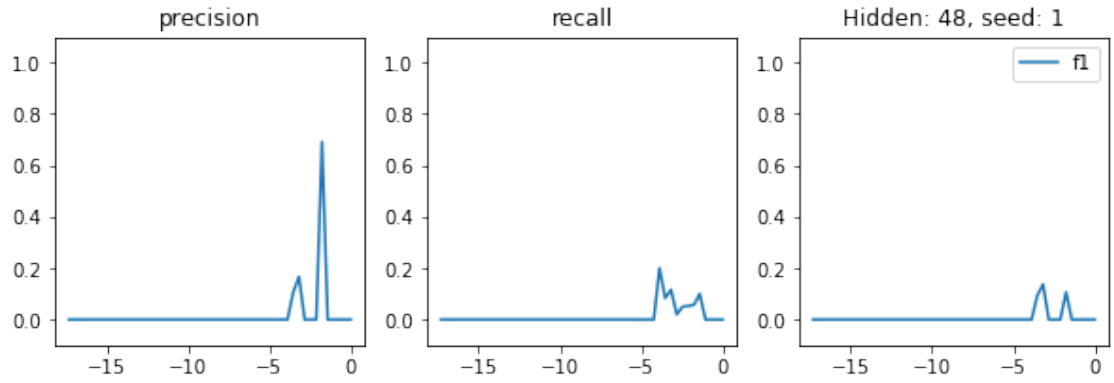

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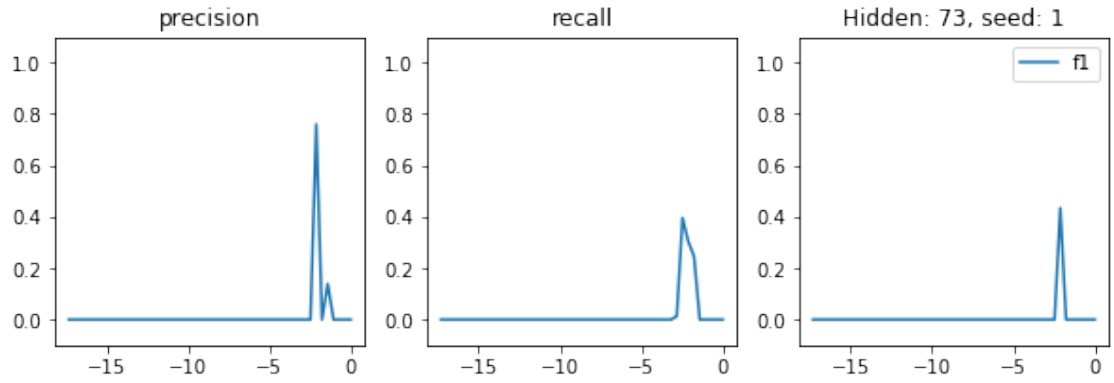
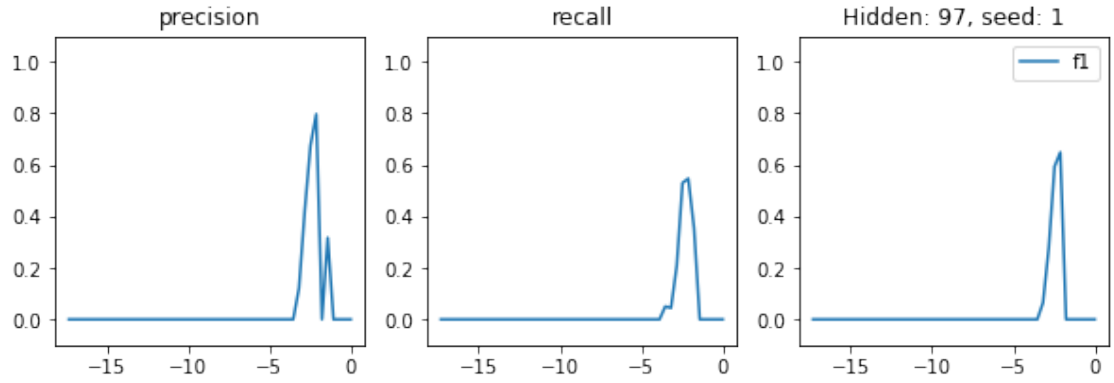
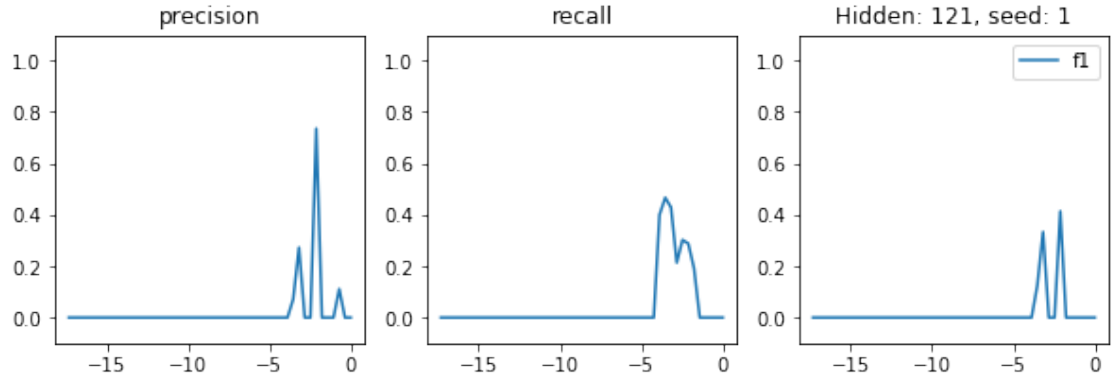


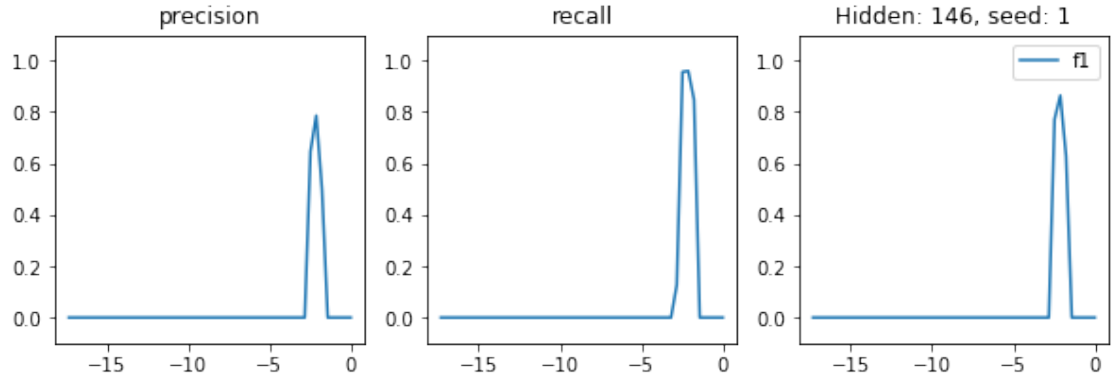
`hidden_size: 97`



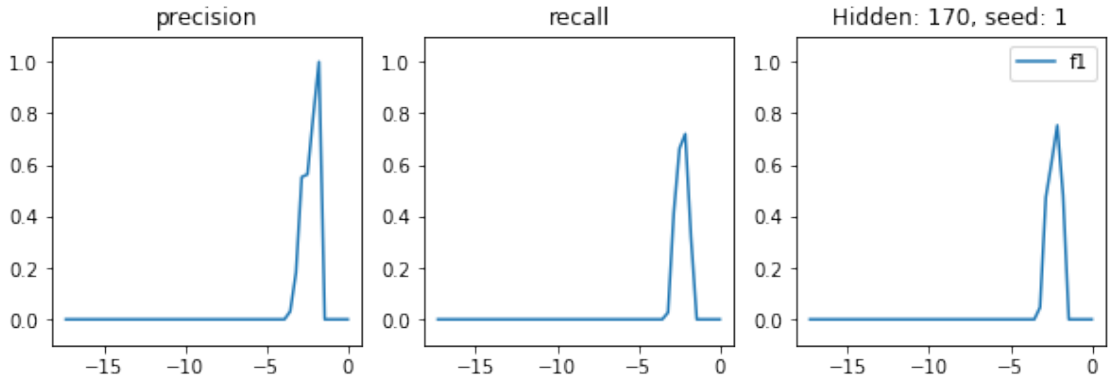
`hidden_size: 121`



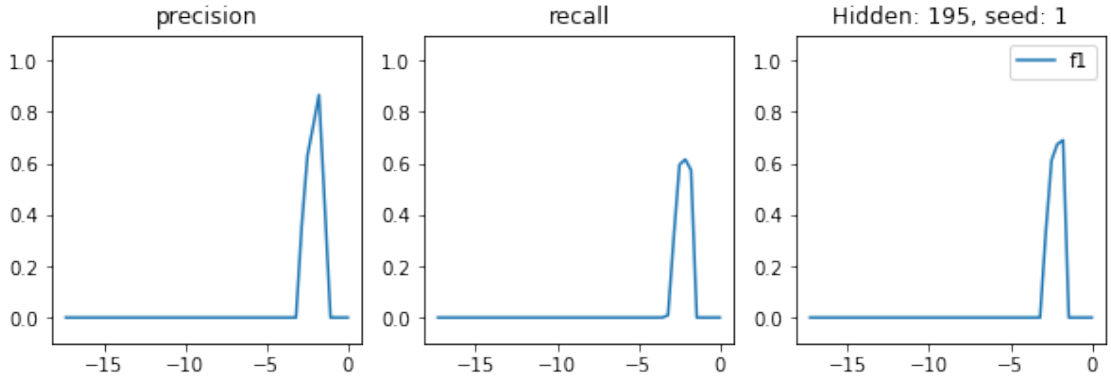
`hidden_size: 146`



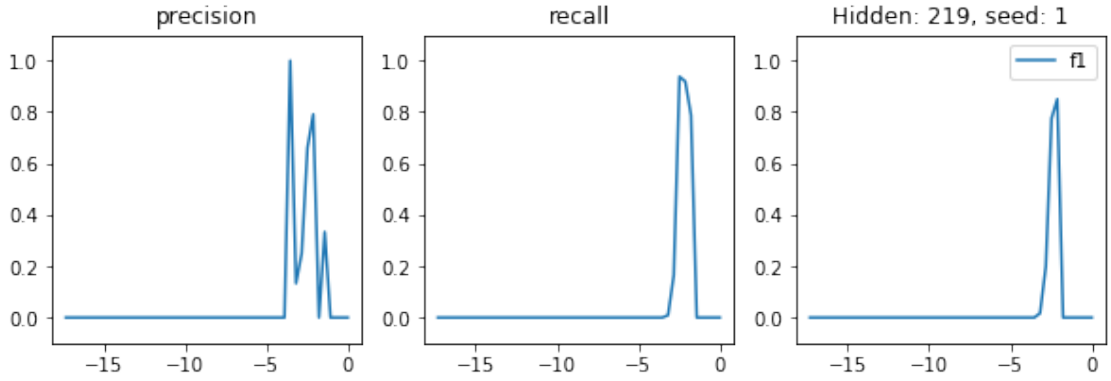
`hidden_size: 170`



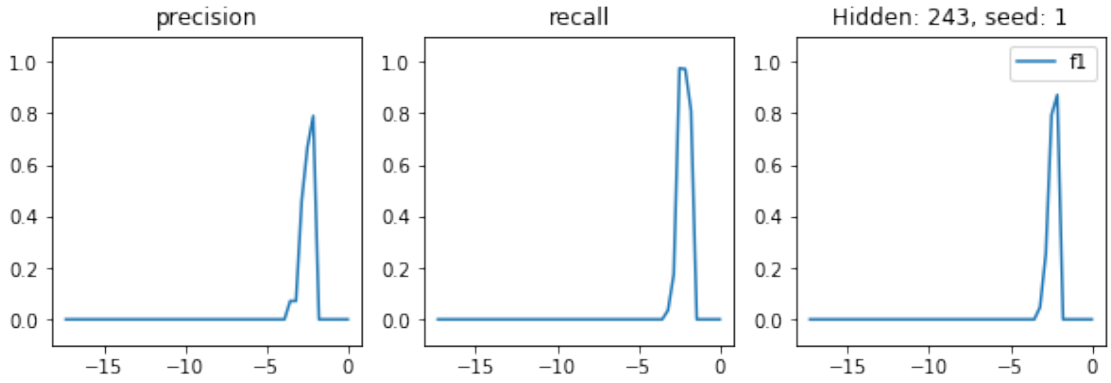
`hidden_size: 195`



`hidden_size: 219`



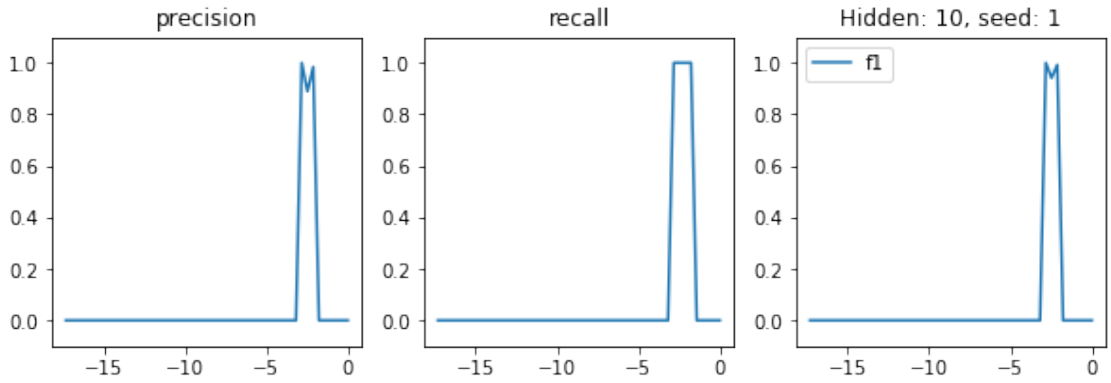
`hidden_size: 243`



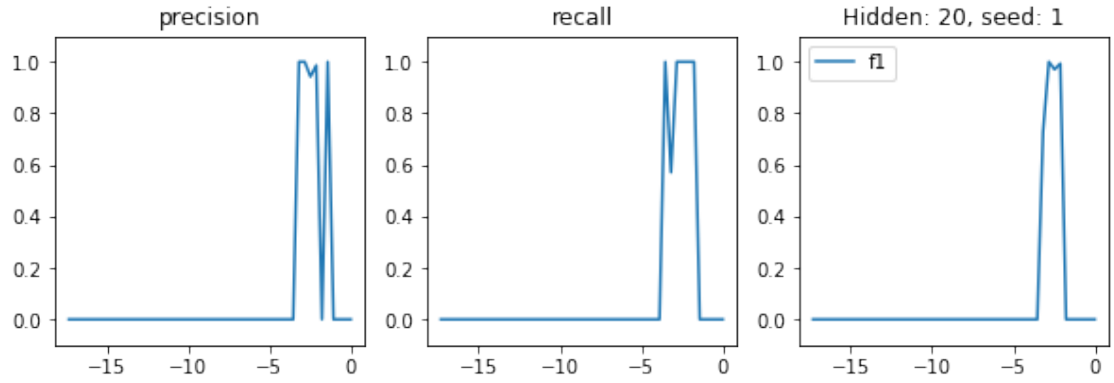
[776]:
```
hidden_sizes = hidden_sizes_lstm

loss_main["lstm"] = get_loss_dict1 (trace, "/media/arjun/Shared/chaos/
 ↪output_files_v2/lstm",
                                    hidden_sizes=hidden_sizes, plot_graphs=True)
```

```
relevance threshold: 0.3969525474770118
hidden_size: 10
```




```
hidden_size: 20
```



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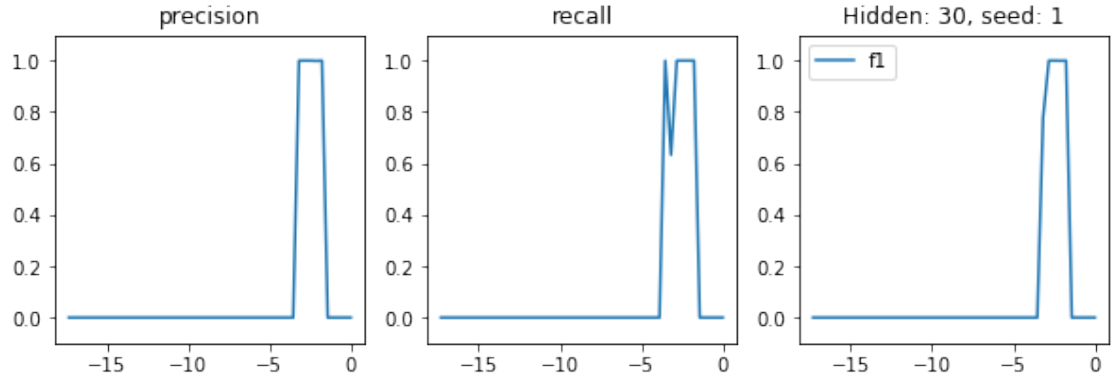

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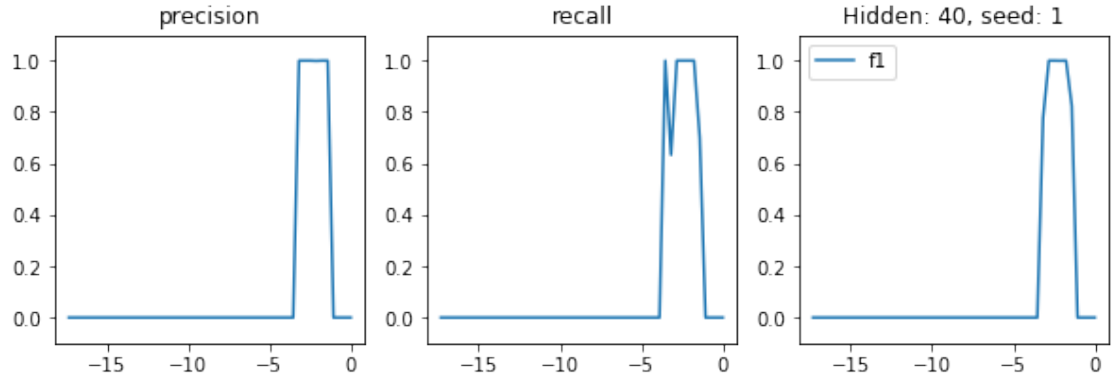

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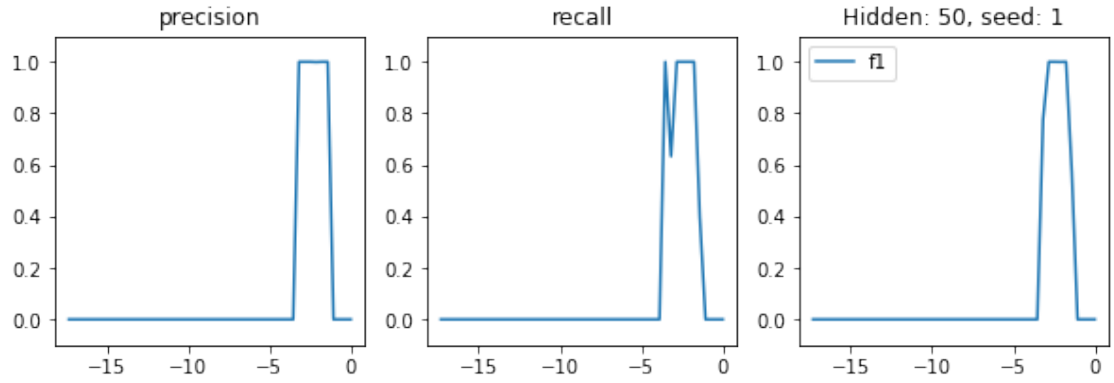

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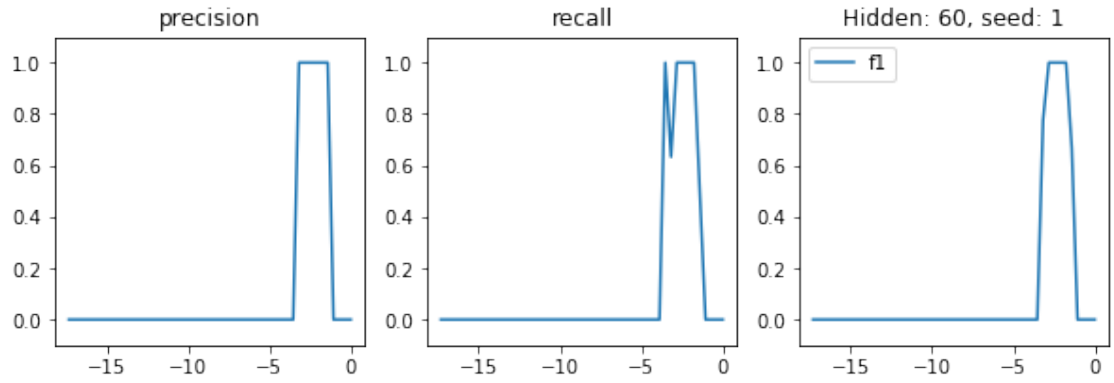

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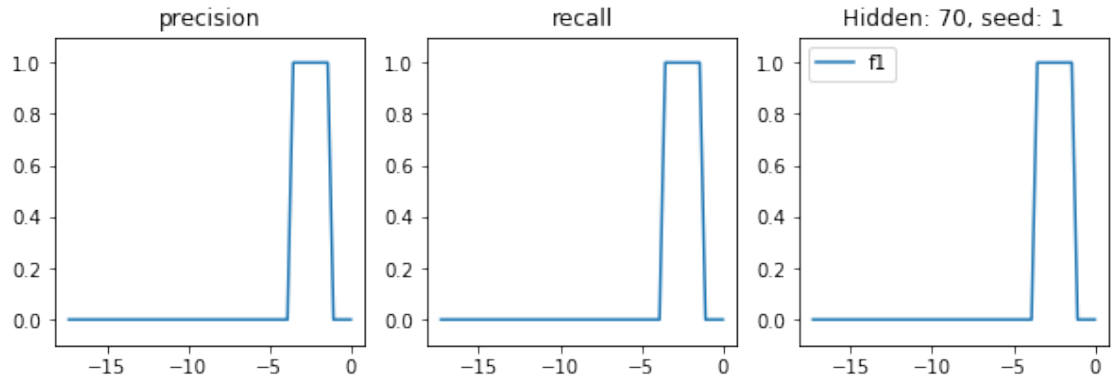

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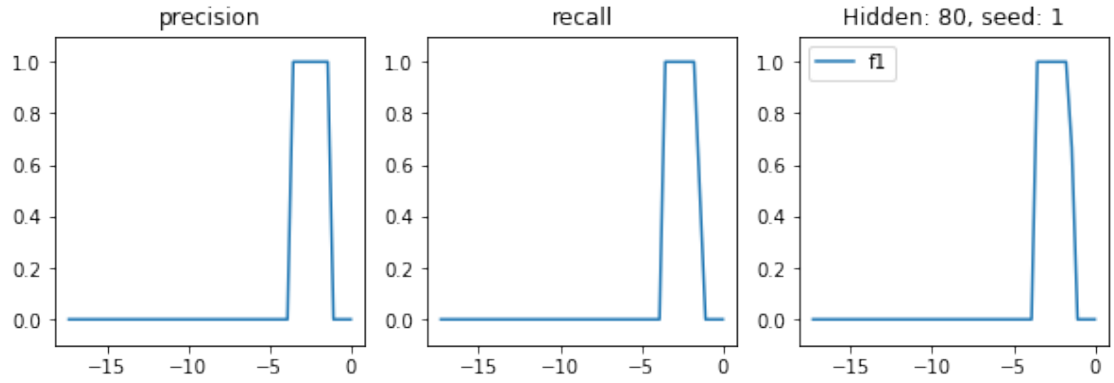

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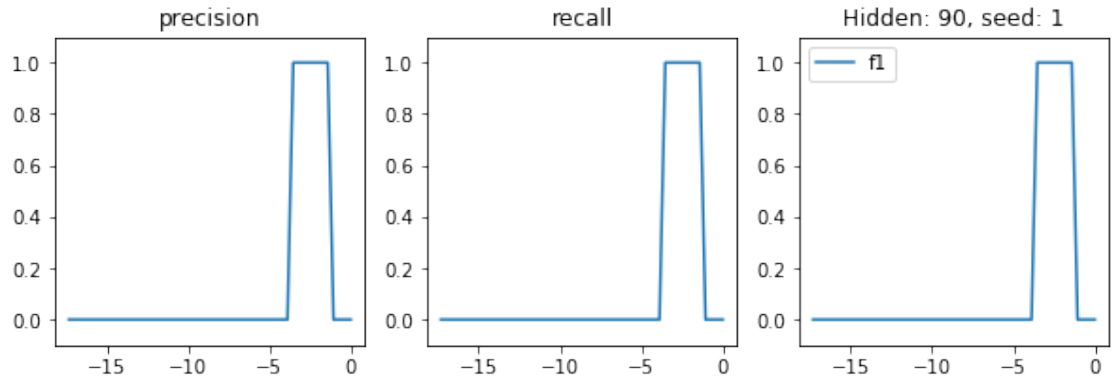

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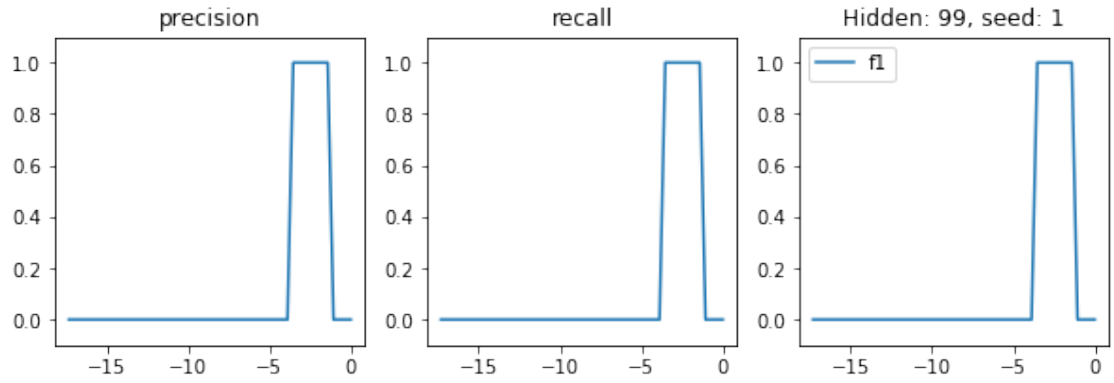

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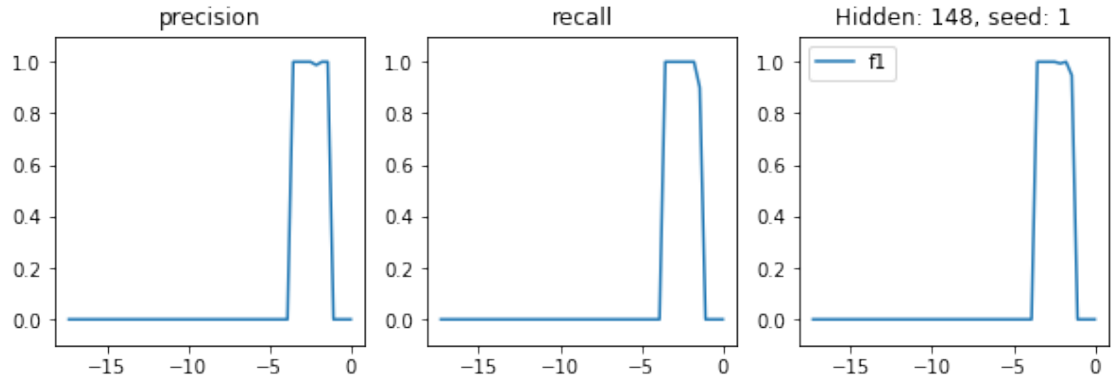

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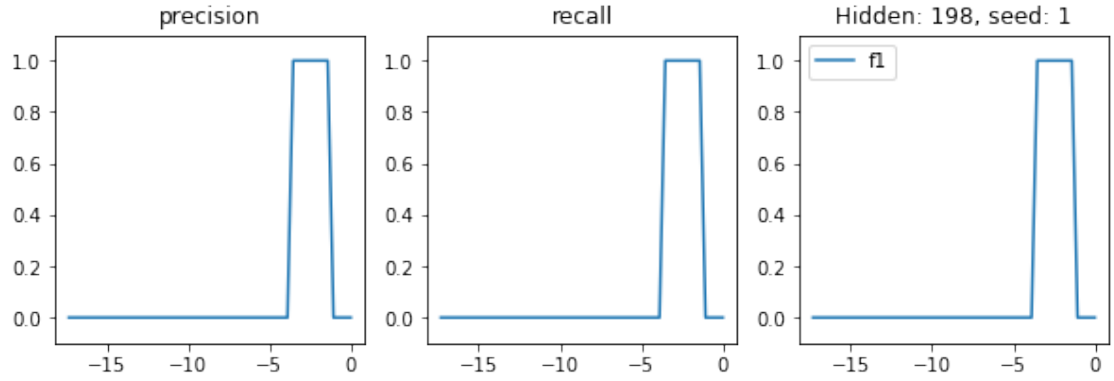

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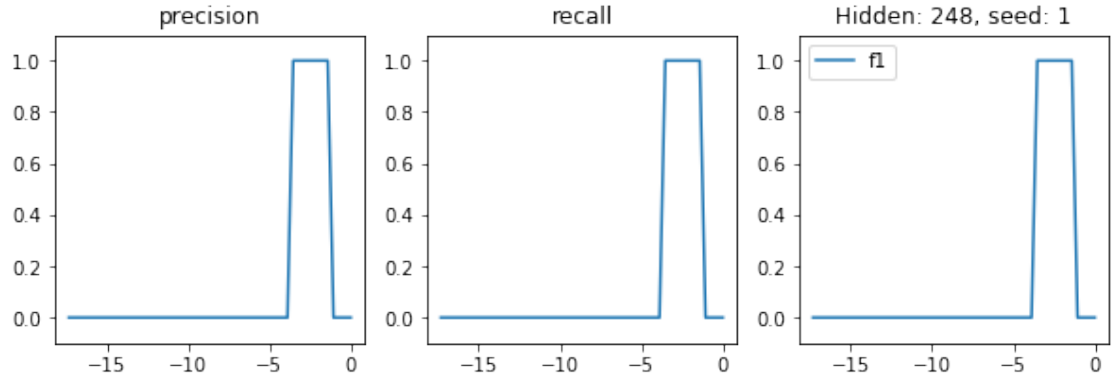

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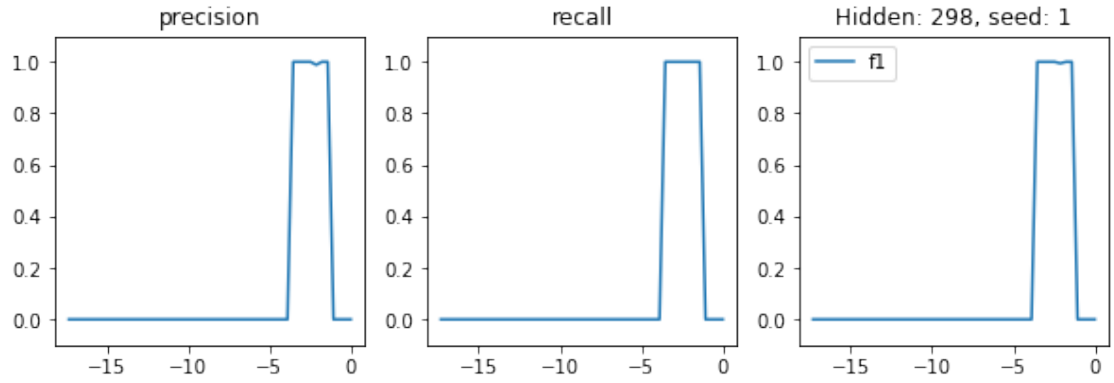

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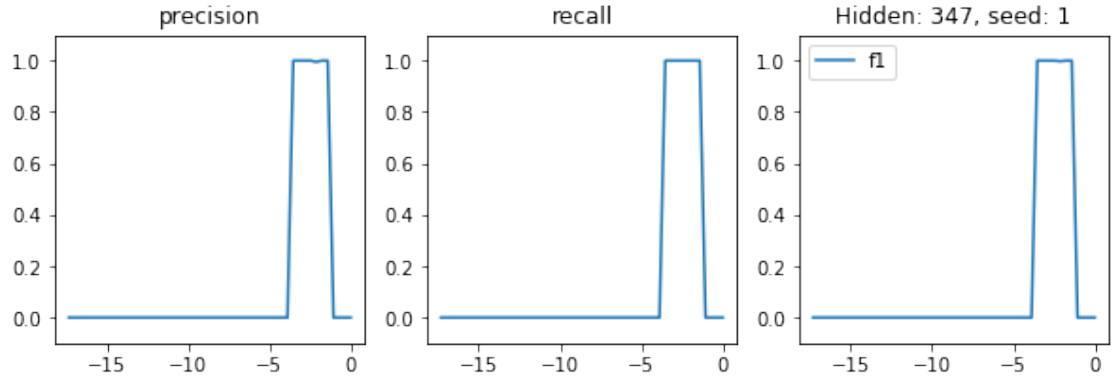

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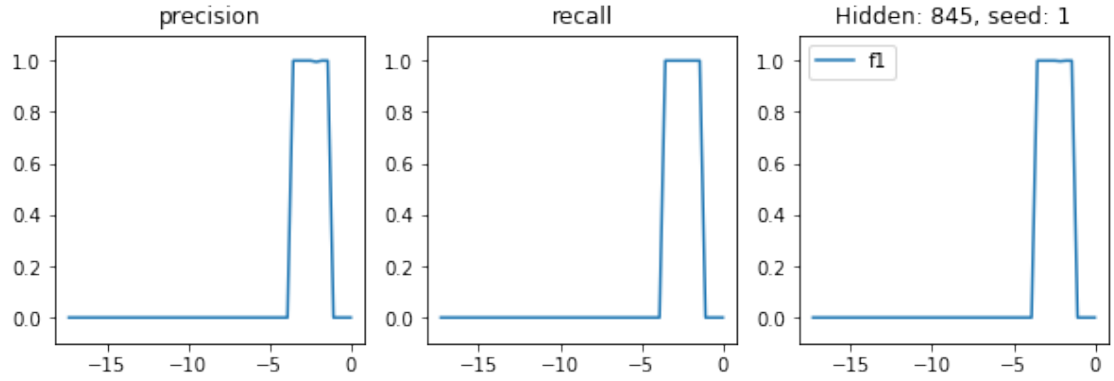

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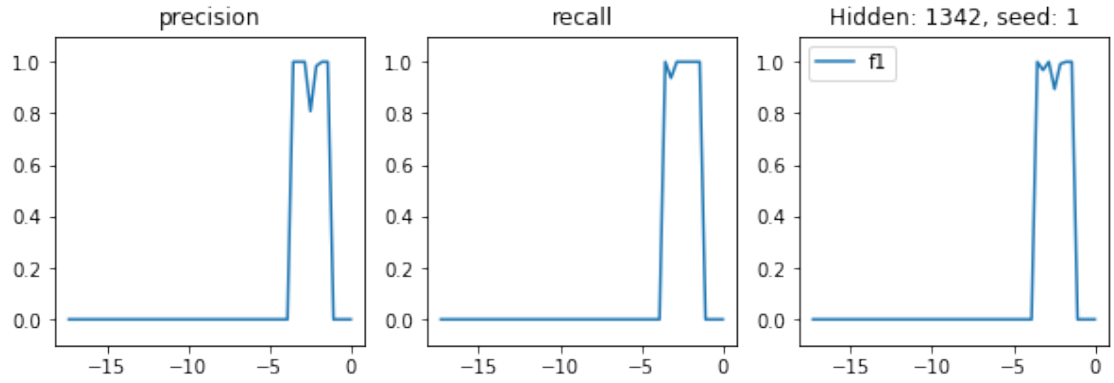

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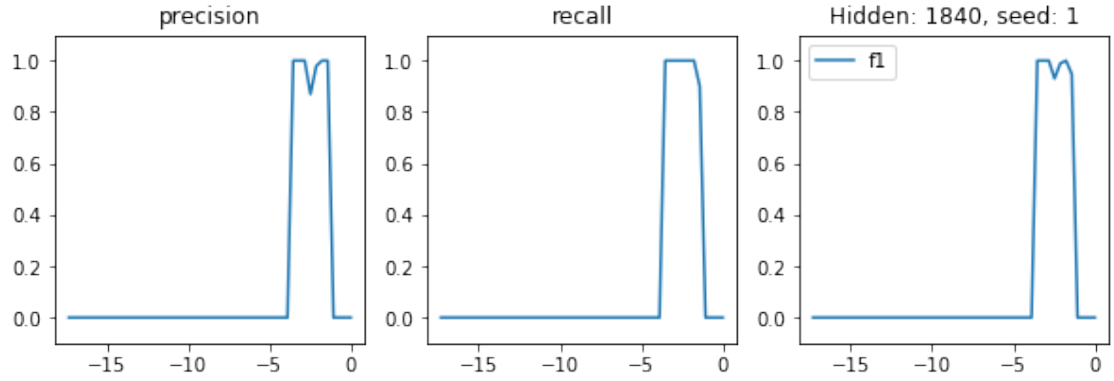

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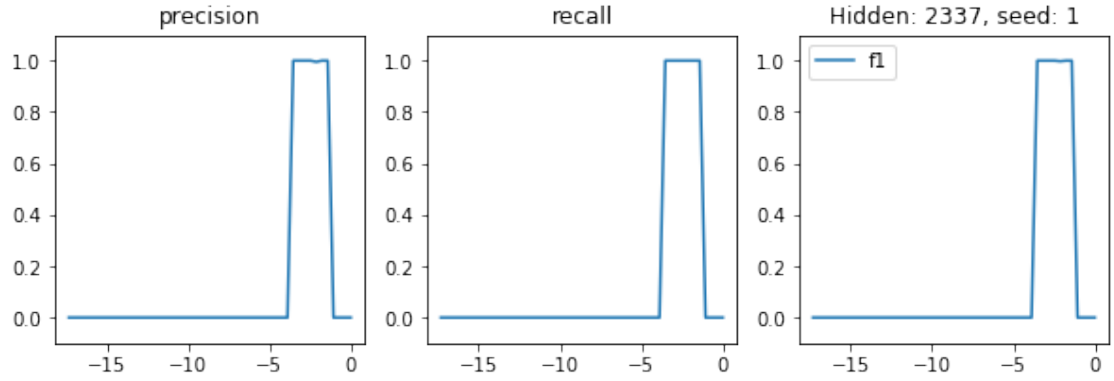
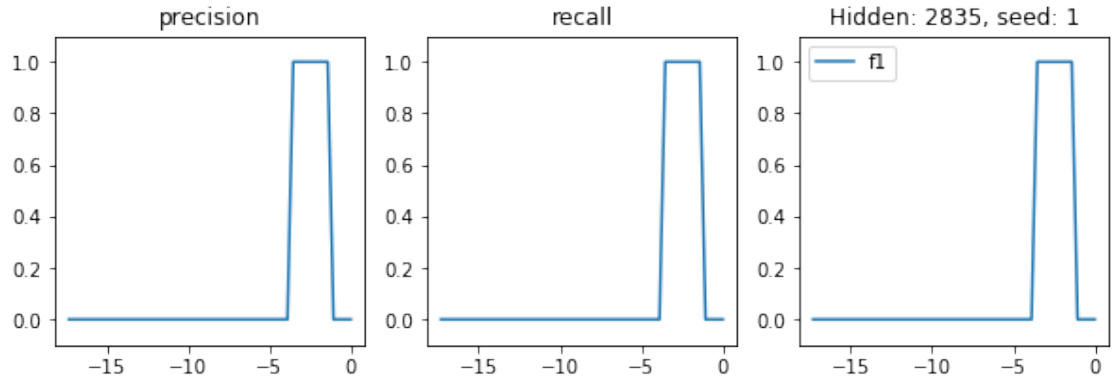
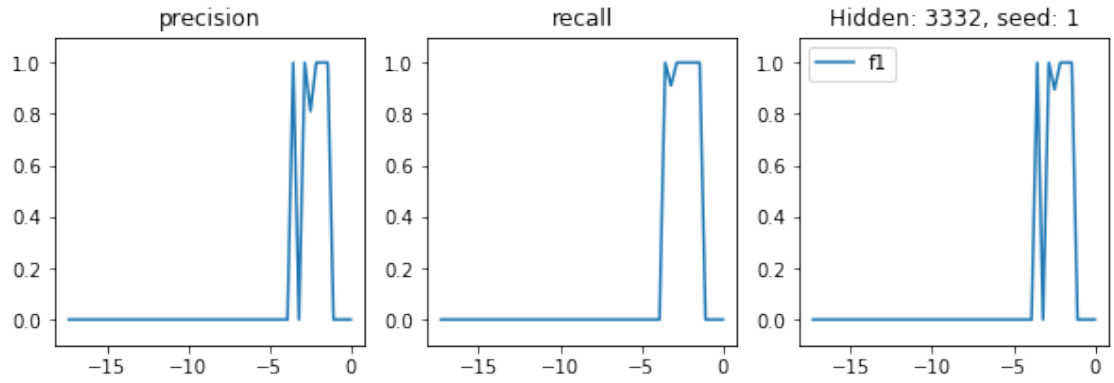


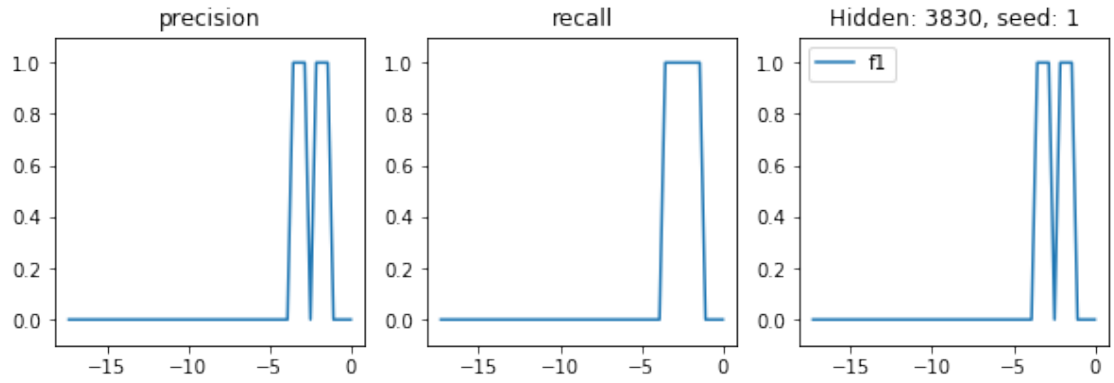
`hidden_size: 2835`



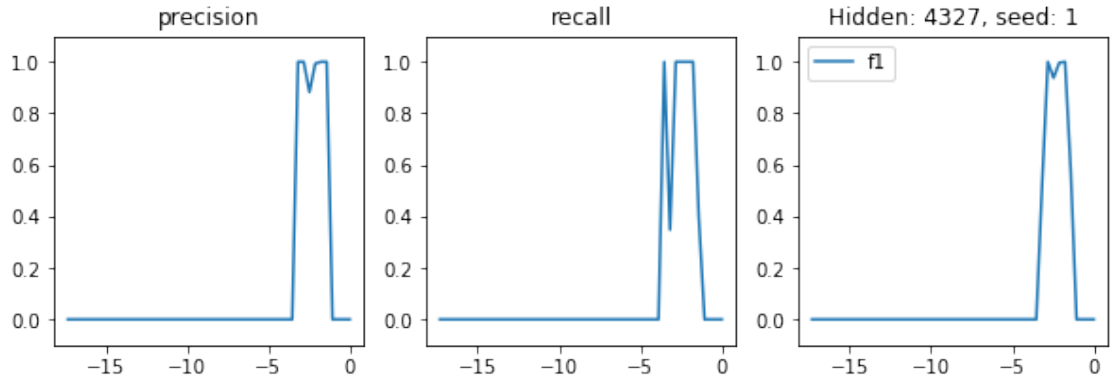
`hidden_size: 3332`



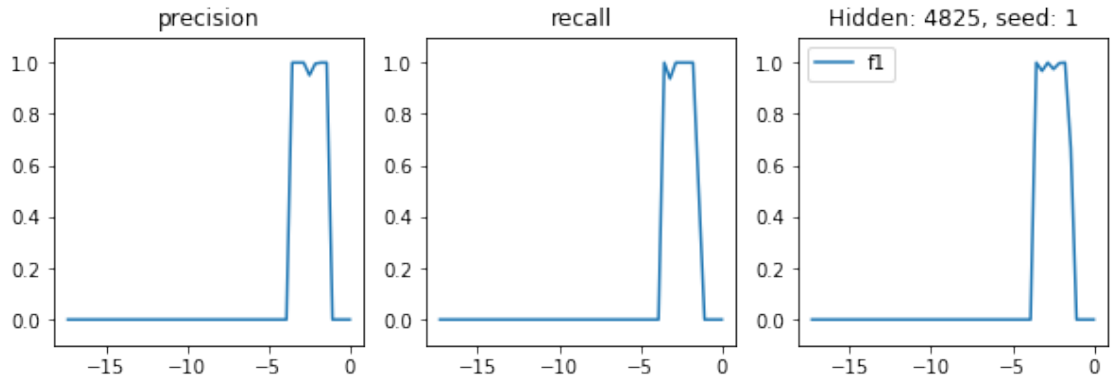
`hidden_size: 3830`



`hidden_size: 4327`




```
hidden_size: 4825
```

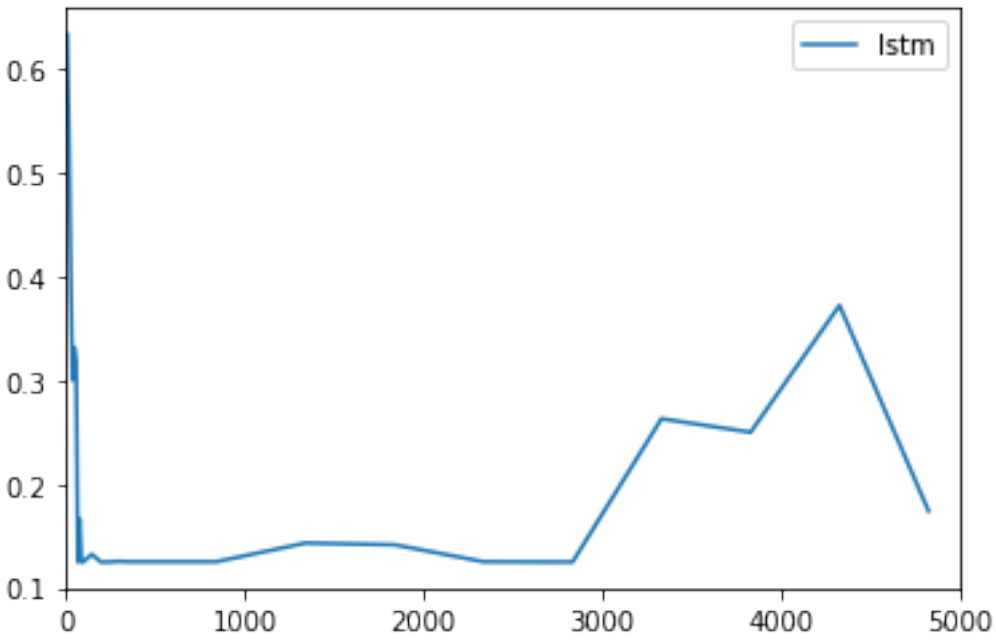


[777]:
```
rademacher_list_fcn = []
rademacher_list_lstm = []

for hidden_size in hidden_sizes_fcn:
    loss_array = loss_main["fcn"][hidden_size]
    rademacher_list_fcn.append(get_rademacher(loss_array))


for hidden_size in hidden_sizes_lstm:
    loss_array = loss_main["lstm"][hidden_size]
    rademacher_list_lstm.append(get_rademacher(loss_array))
```

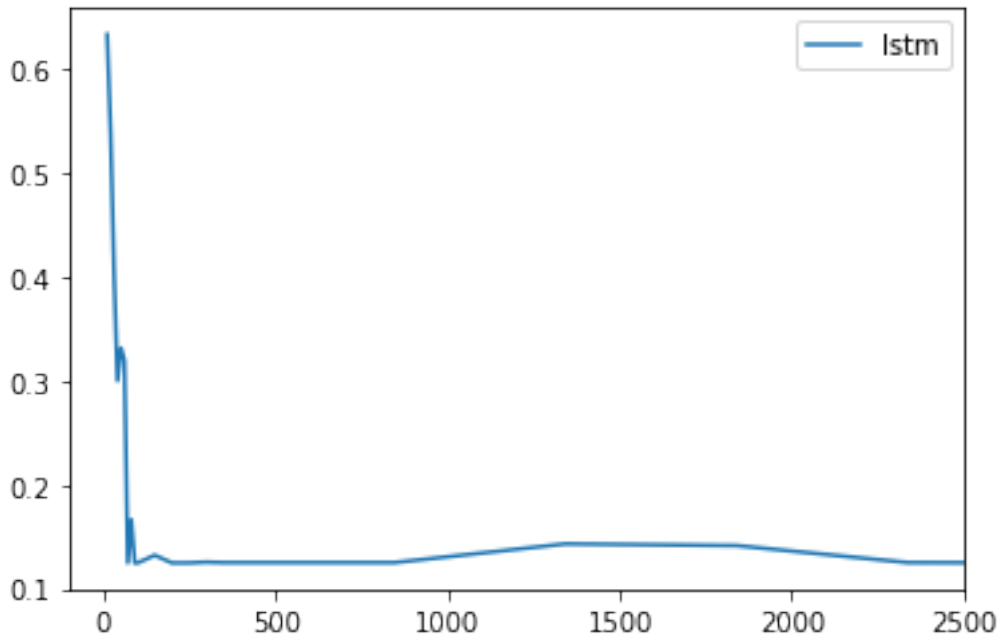
[778]:
```
# compute number of parameters
fcn_param_list = []
lstm_param_list = []

for idx, hidden_size in enumerate(hidden_sizes_fcn):
```

```
    fcn_param_list.append(compute_parameters.get_count(4000, 100, [␣
 ↪hidden_sizes_fcn[idx] ], [ 'fcn' ]))

for idx, hidden_size in enumerate(hidden_sizes):
    lstm_param_list.append(compute_parameters.get_count(100, 100, [100,␣
 ↪hidden_sizes_lstm[idx]], ["lstm", "fcn"]))
```

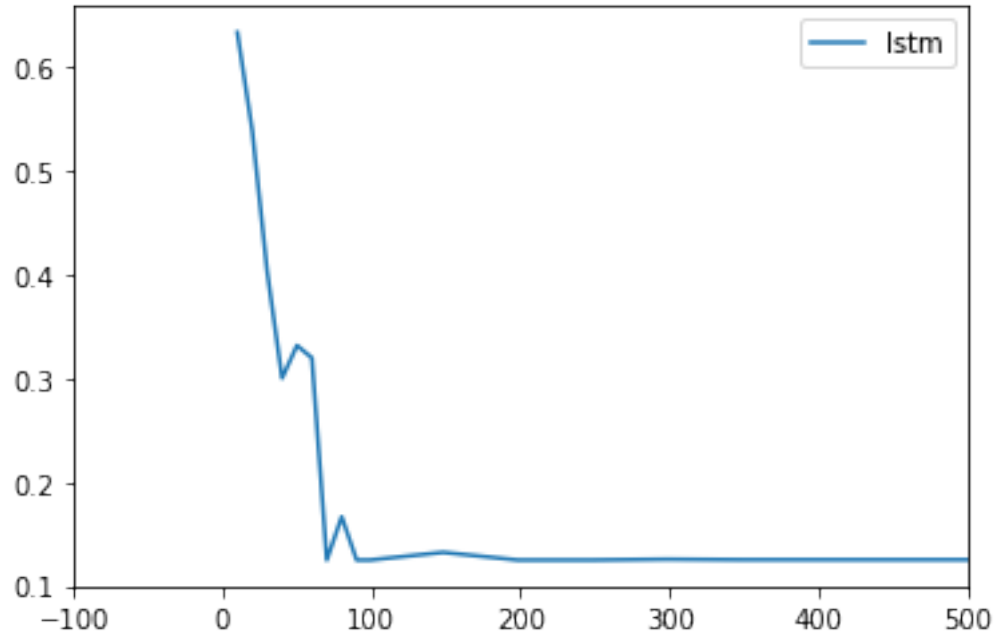
[779]:
```
# plt.plot(fcn_param_list, rademacher_list_fcn, label="fcn")
plt.plot(hidden_sizes_lstm, rademacher_list_lstm, label="lstm")
plt.legend()
# plt.ylim((0.8, 1.1))
plt.xlim((-0, 5000))
plt.show()
```



[785]:
```
# plt.plot(fcn_param_list, rademacher_list_fcn, label="fcn")
plt.plot(hidden_sizes_lstm, rademacher_list_lstm, label="lstm")
plt.legend()
# plt.ylim((0.8, 1.1))
plt.xlim((-100, 2500))
plt.show()
```

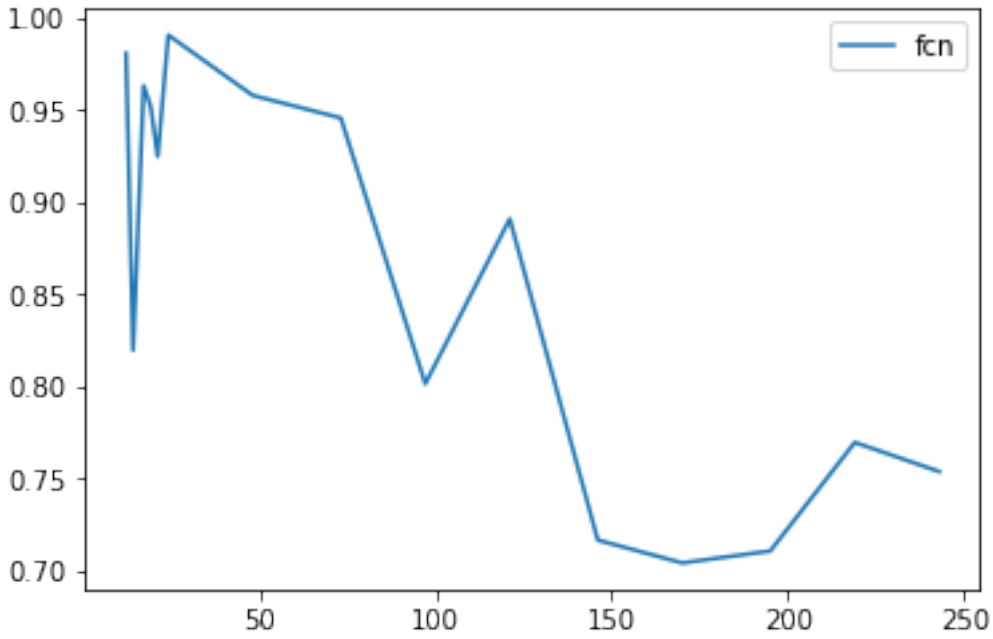


[787]:
```
# plt.plot(fcn_param_list, rademacher_list_fcn, label="fcn")
plt.plot(hidden_sizes_lstm, rademacher_list_lstm, label="lstm")
plt.legend()
# plt.ylim((0.8, 1.1))
plt.xlim((-100, 500))
plt.show()
```



[782]:
```
plt.plot(hidden_sizes_fcn, rademacher_list_fcn, label="fcn")
plt.legend()
```

[782]:
```
<matplotlib.legend.Legend at 0x7f9b5e80b710>
```

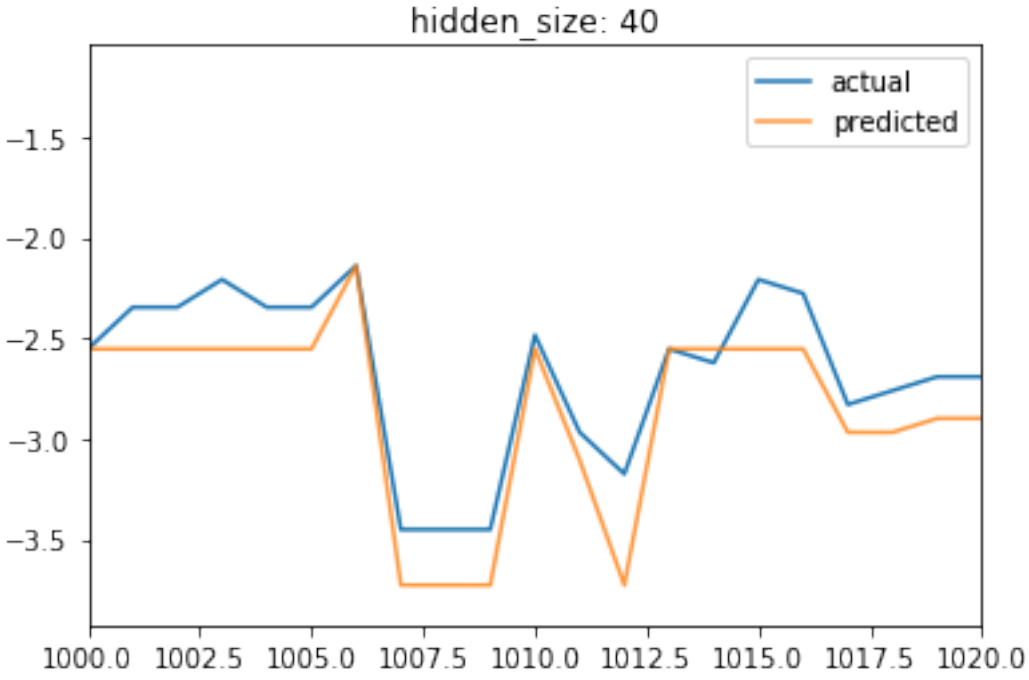


[781]:
```
actual = []
predicted = []
actual = [ val[0] for val in data ]
predicted = [ val[1] for val in data ]


for hidden_size in hidden_sizes_lstm:
    data = get_actual_predicted(trace, trace_name, jvm,␣
 ↪hidden_size=hidden_sizes_lstm[2], history_size=40,
                                model_type="lstm", output_file_location="/media/
 ↪arjun/Shared/chaos/output_files_v2/lstm")

    plt.plot(actual, label="actual")
    plt.plot(predicted, label="predicted", alpha=0.8)
    plt.title("hidden_size: {}".format(hidden_size))
    plt.xlim((1000, 1020))
    plt.legend()
    plt.show()
```

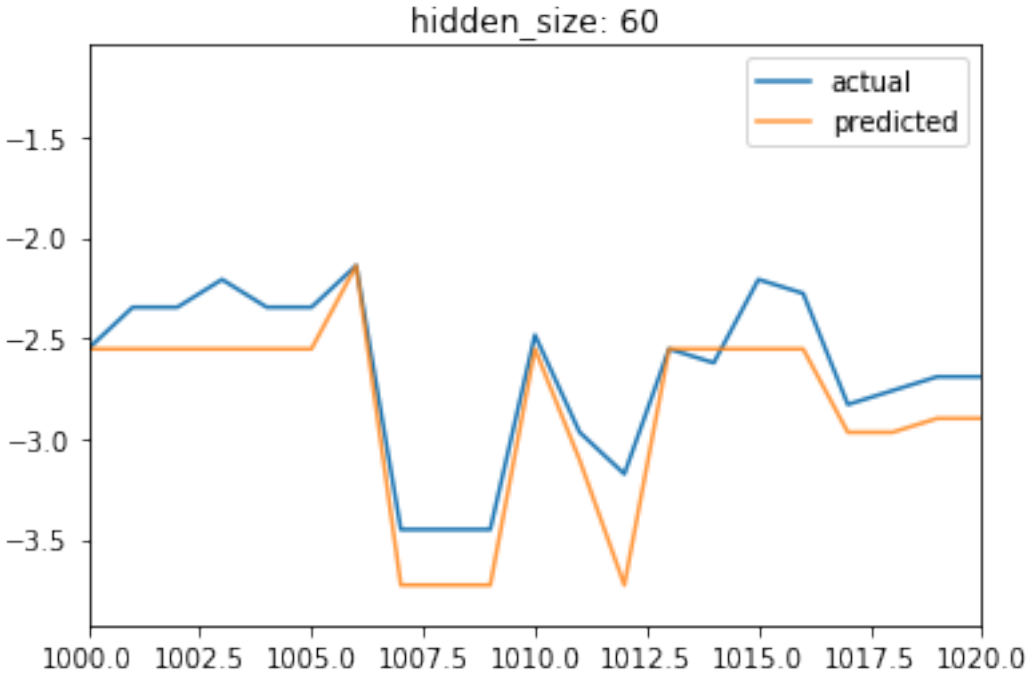

hidden_size: 10
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0


hidden_size: 20
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0


hidden_size: 30
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

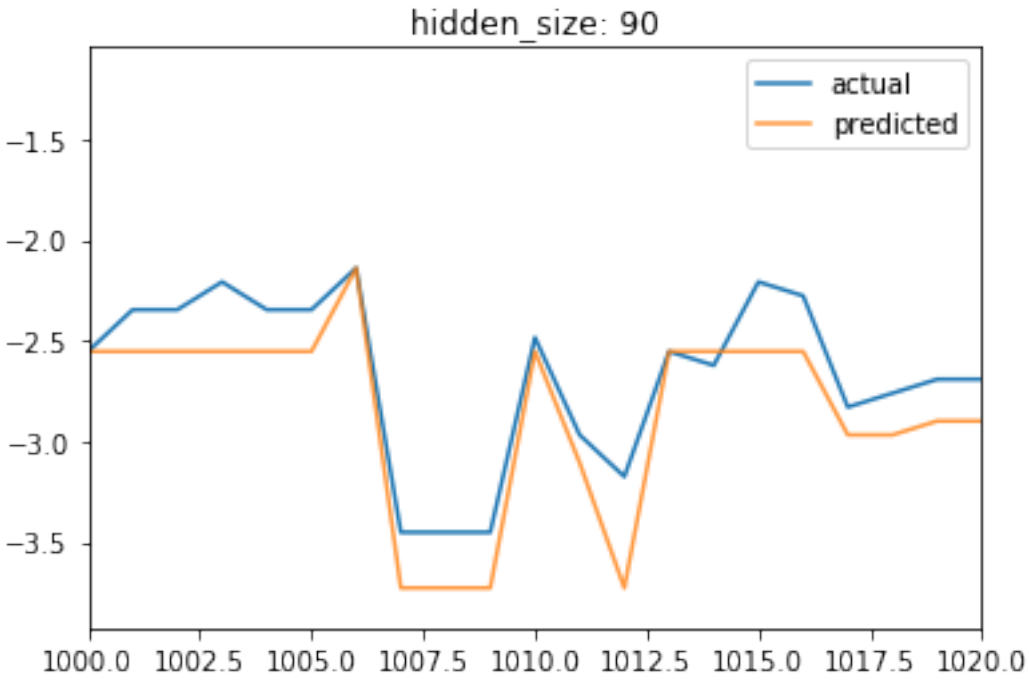

hidden_size: 40
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

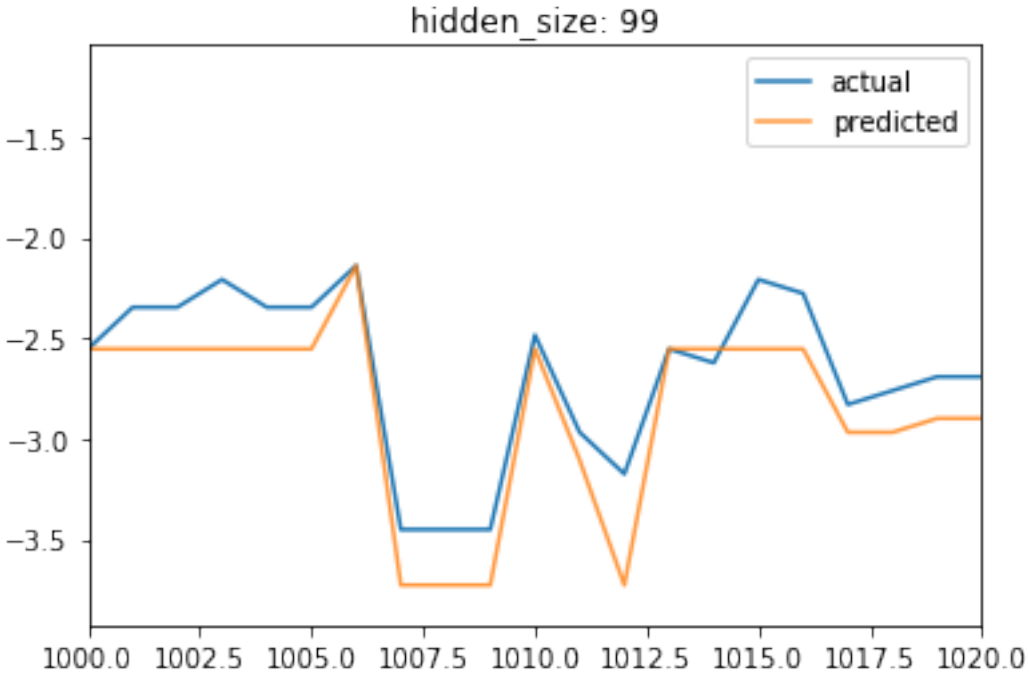

hidden_size: 50
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

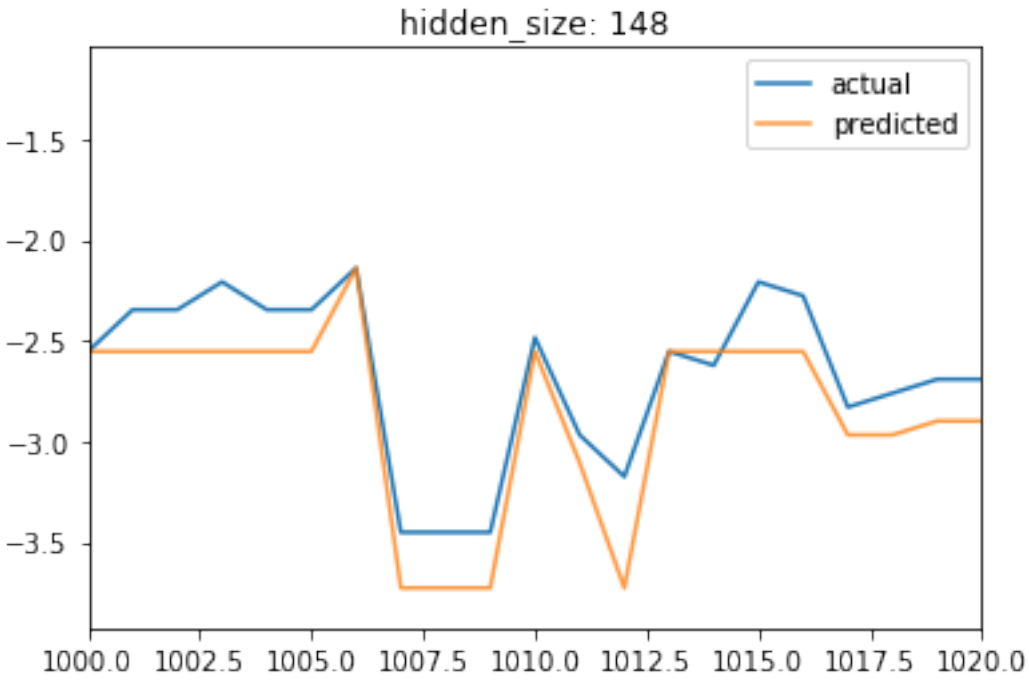

hidden_size: 60
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

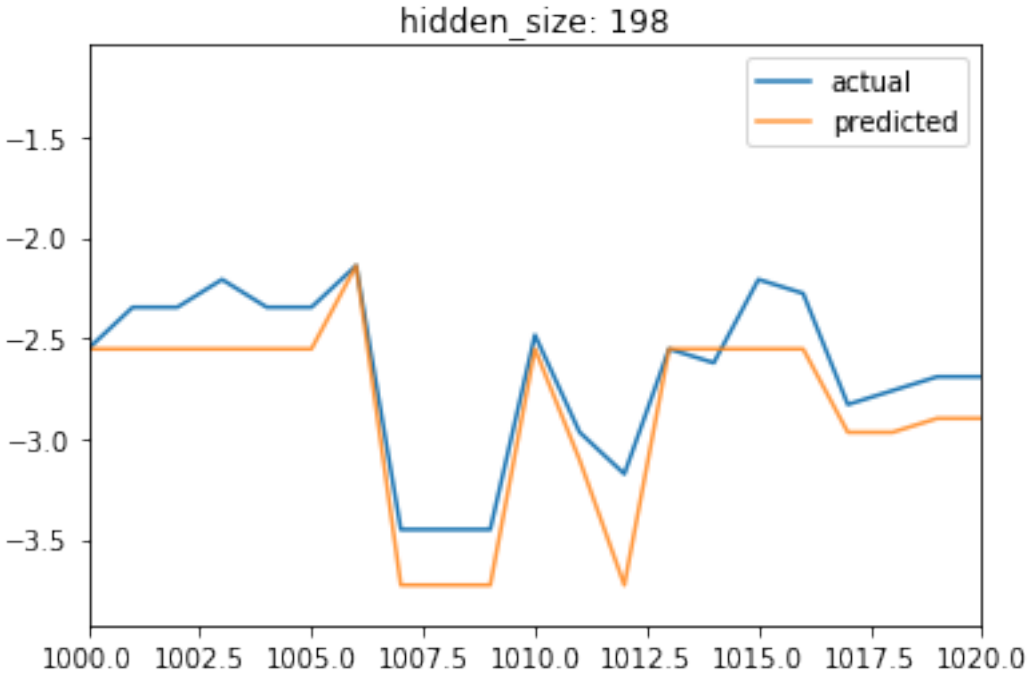

hidden_size: 70
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

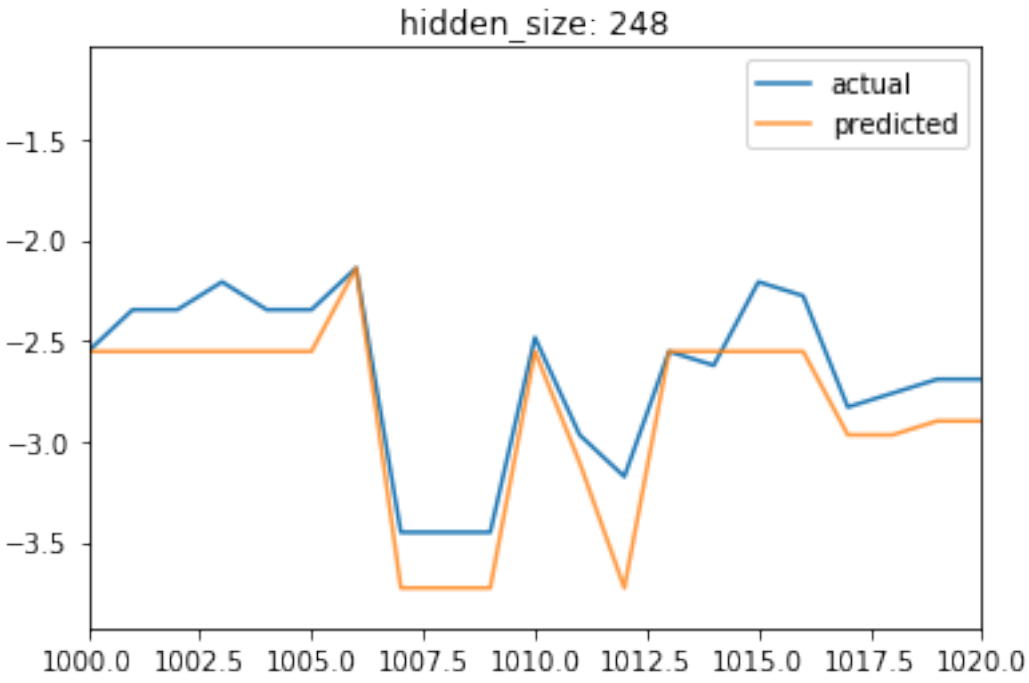

hidden_size: 80
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

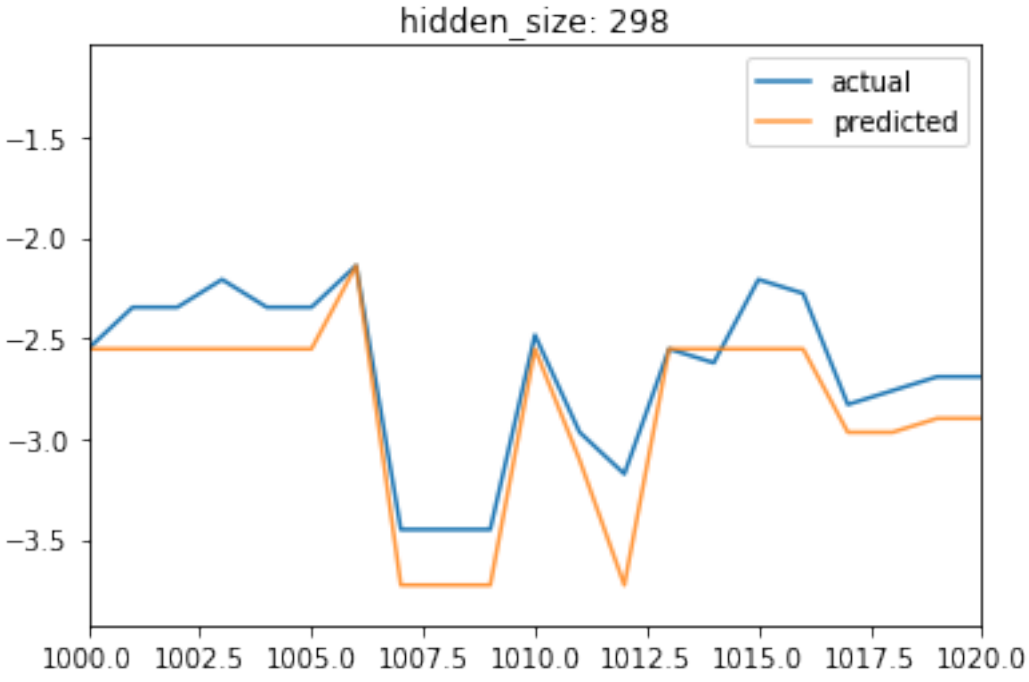

hidden_size: 90
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

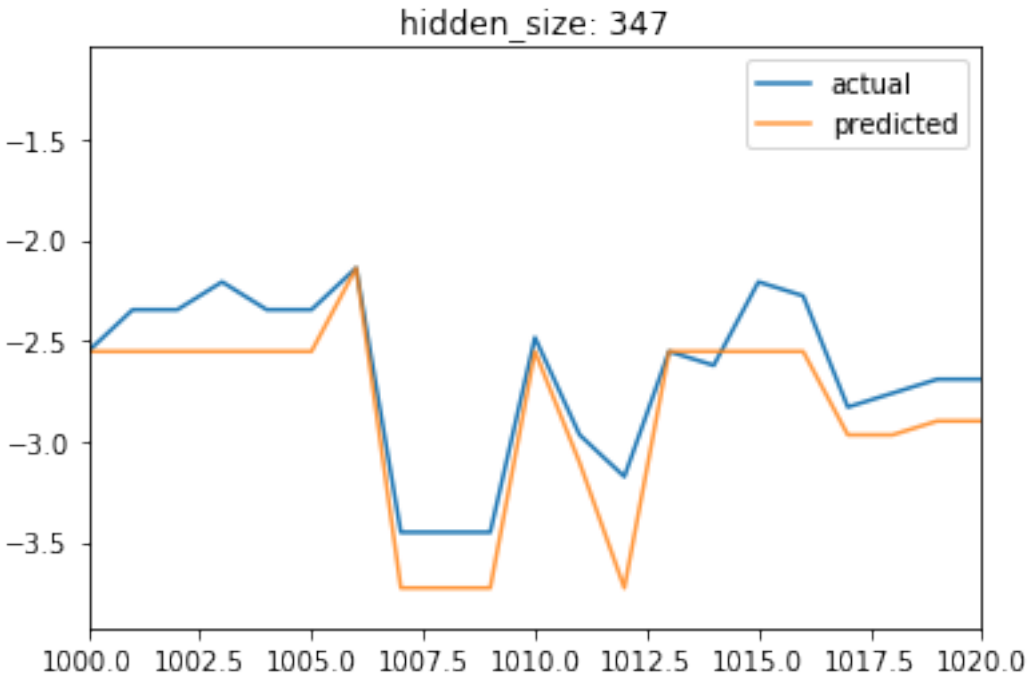

hidden_size: 99
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

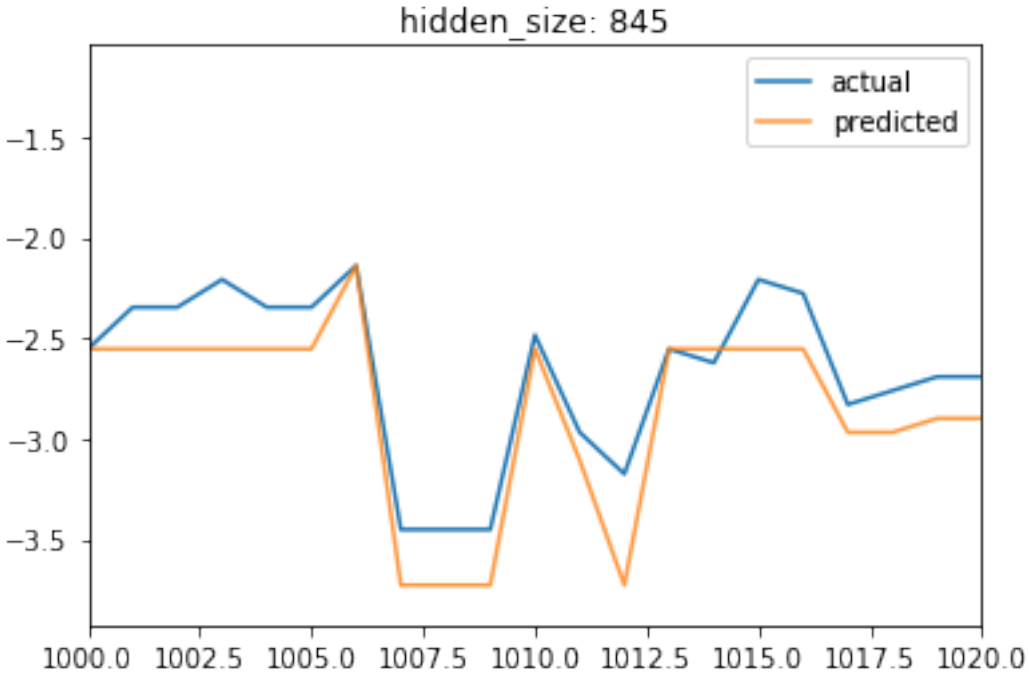

hidden_size: 148
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

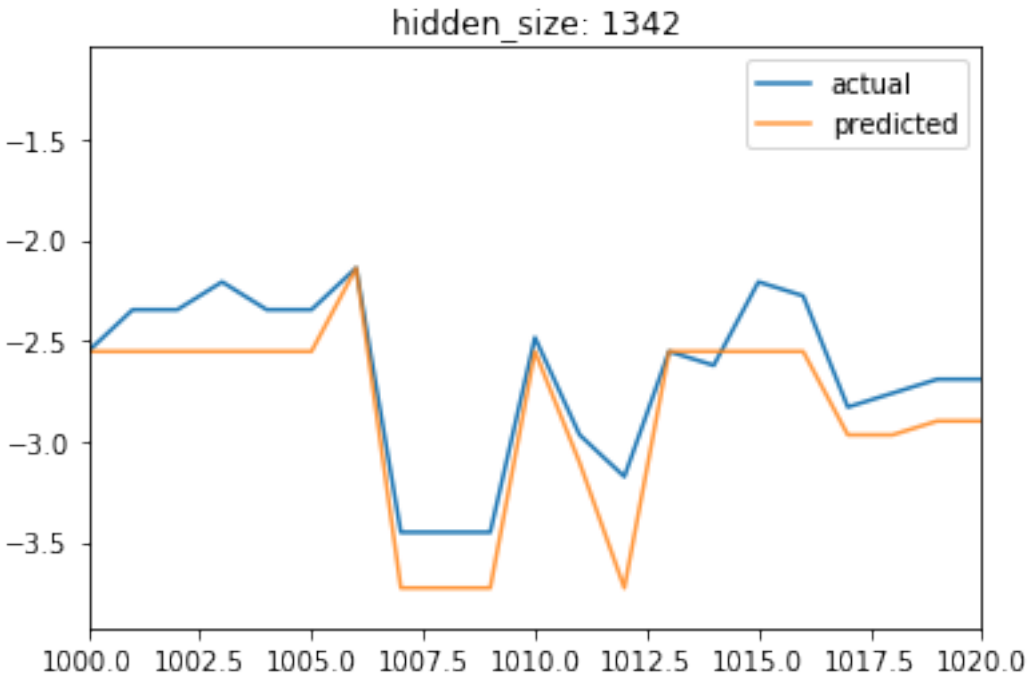

hidden_size: 198
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

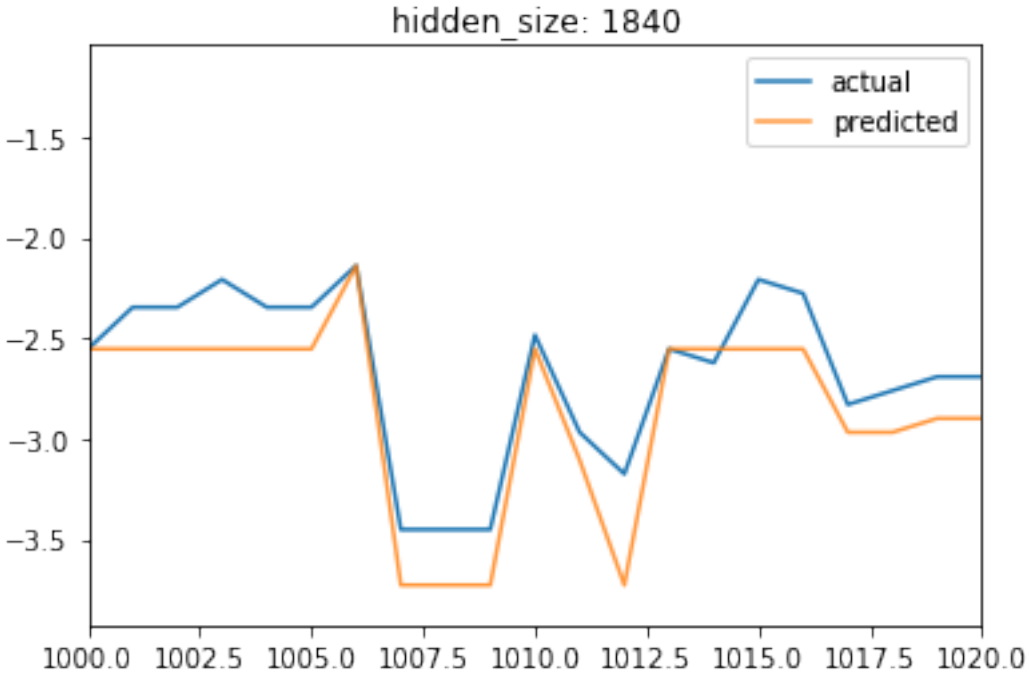

hidden_size: 248
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

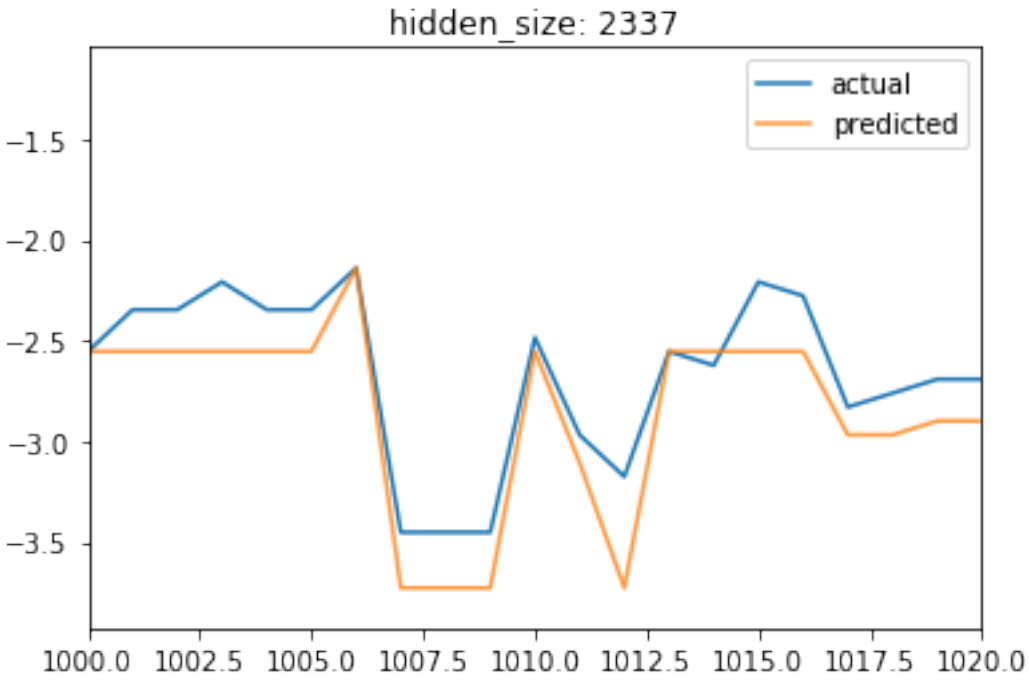

hidden_size: 298
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

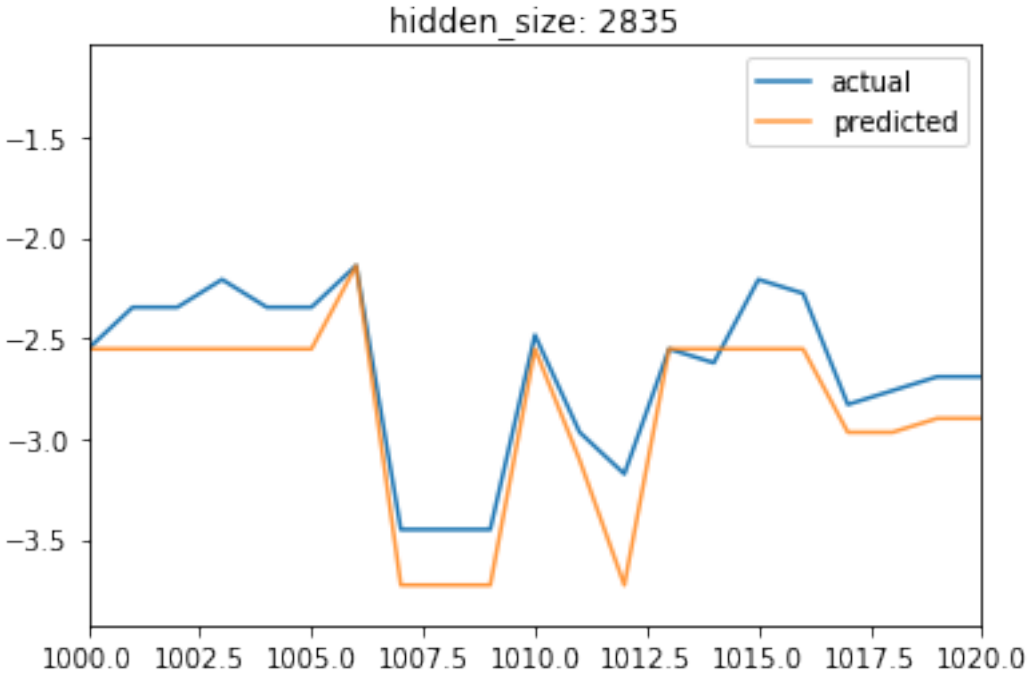

hidden_size: 347
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

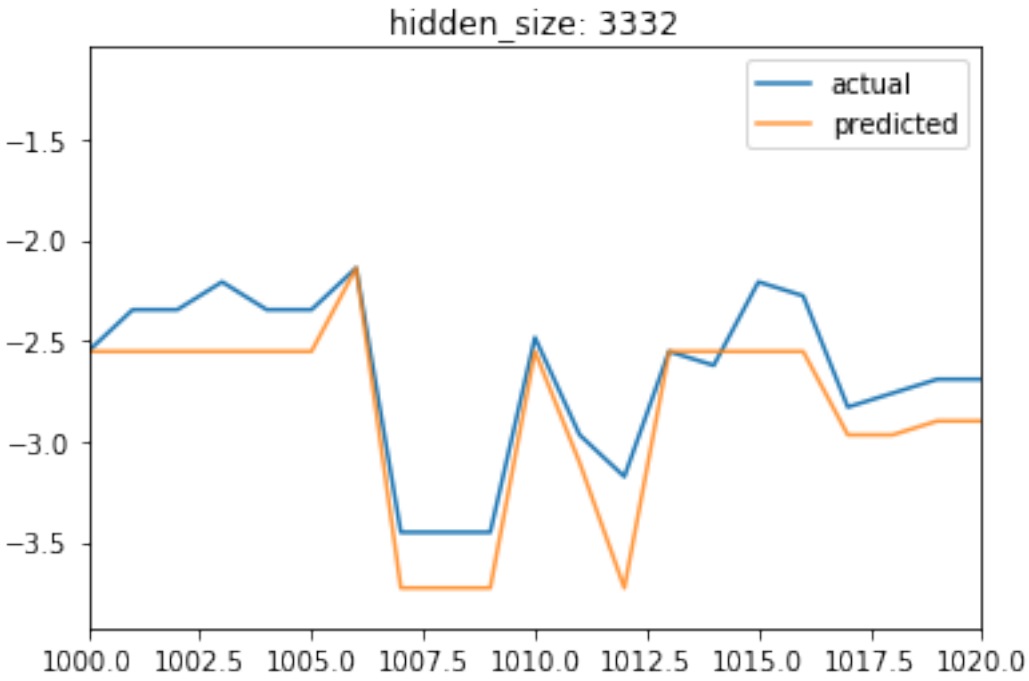

hidden_size: 845
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

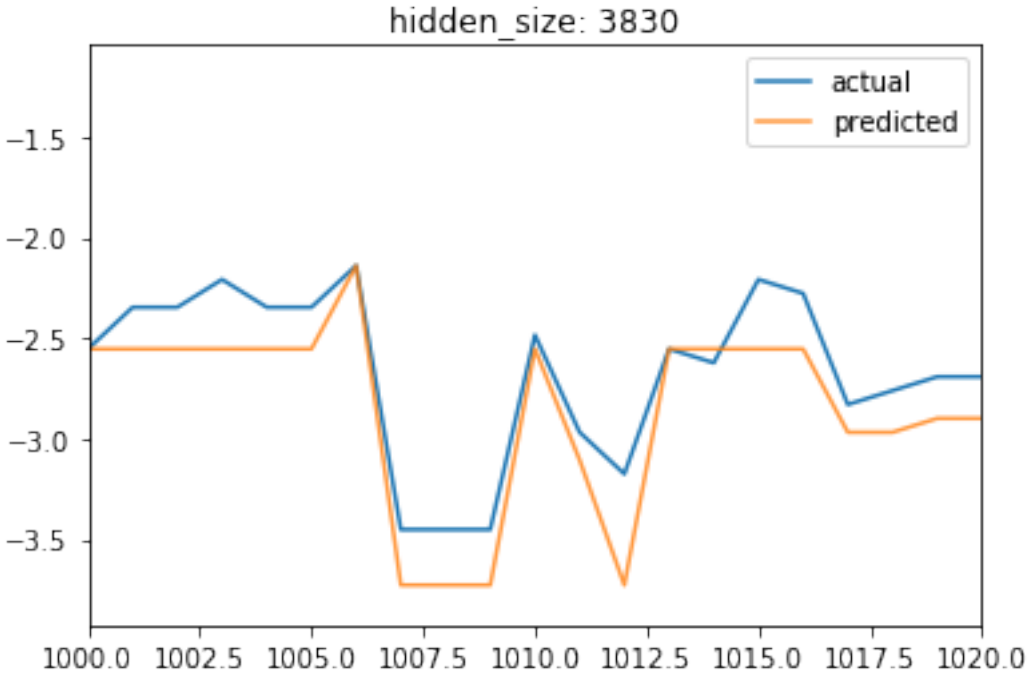

hidden_size: 1342
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

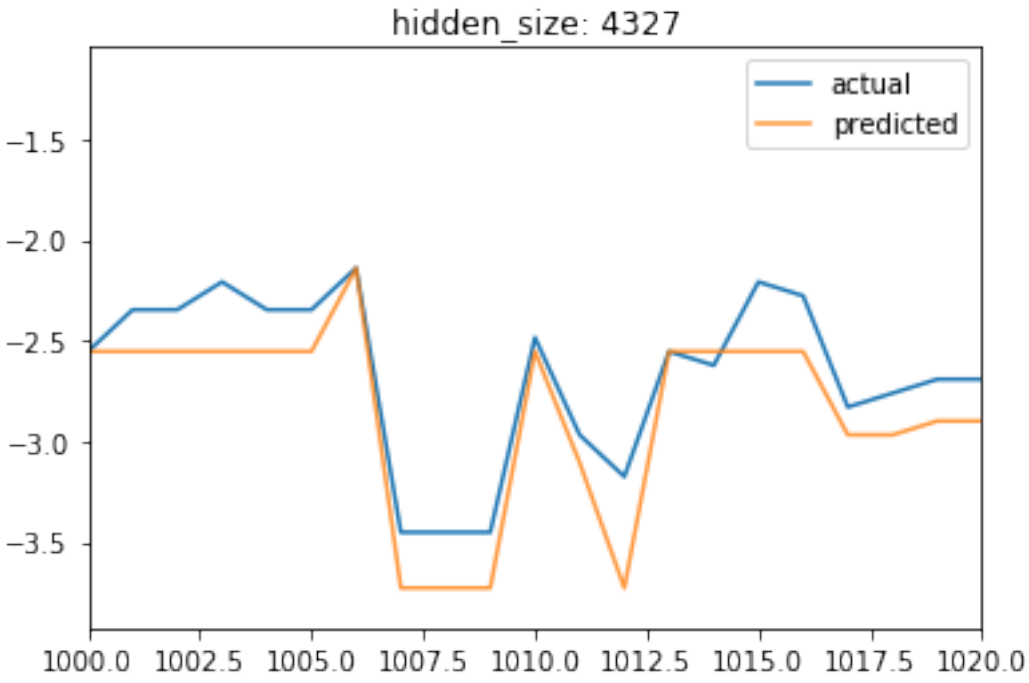

hidden_size: 1840
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0

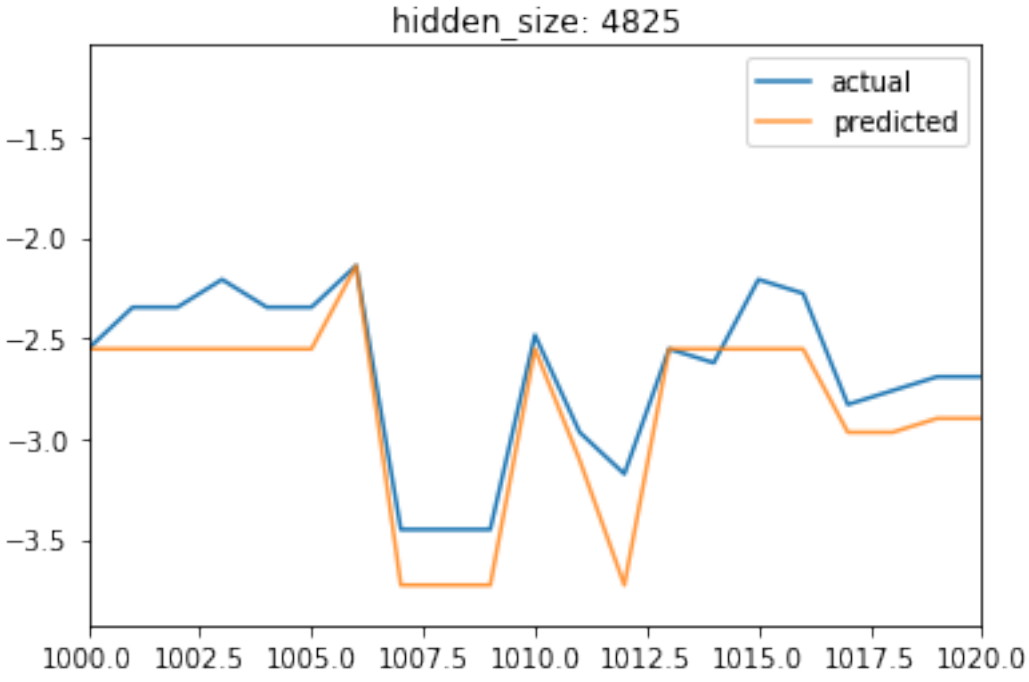

hidden_size: 2337
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0


hidden_size: 2835
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0


hidden_size: 3332
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0


hidden_size: 3830
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0


hidden_size: 4327
actual
predicted
−1.5
−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0


hidden_size: 4825
actual
predicted
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−2.0
−2.5
−3.0
−3.5
1000.0
1002.5
1005.0
1007.5
1010.0
1012.5
1015.0
1017.5
1020.0