Prof. Dr. L. Paditz, 15.02.2019

HTW Dresden,

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Lineare Regression mit Grafik

(y-Daten sind verrauschte sin-Daten)

lin. Modell: y=W*x+b

=================================

später:

Weiterführend allg. sin-Modell mit verrauschten Daten:

y=a*sin(b*x+c)+d, (Paditz 13.03.2019)

Quelle für lin. Modell: s.S.48-50

http://harmanani.github.io/classes/csc498r/

Notes/Lecture16.pdf

python3

```
# %% imports %matplotlib inline

import numpy as np

import tensorflow as tf

import matplotlib.pyplot as plt

# %% Let's create some toy data

plt.ion()

n_observations = 100

fig, ax = plt.subplots(1, 1)

xs = np.linspace(-3, 3, n_observations)

ys = np.sin(xs) + np.random.uniform(-0.5, 0.5,

n_observations)

ax.scatter(xs, ys)

fig.show()

plt.draw()

# %% tf.placeholders for the input and output of the

network.

# Placeholders are variables which we need to fill in

when we
```

```
# are ready to compute the graph.
X = tf.placeholder(tf.float32)
Y = tf.placeholder(tf.float32)
# %% We will try to optimize min_(W,b) ||(X*w +
b) - y||^2
# The `Variable()` constructor requires an initial value
for the
# variable,, which can be a `Tensor` of any type and
shape. The
# initial value defines the type and shape of the
variable.
# After construction, the type and shape of the
variable are
# fixed. The value can be changed using one of the
assign methods.
W = tf.Variable(tf.random_normal([1]),
name='weight')
b = tf.Variable(tf.random_normal([1]), name='bias')
```

```
Y_pred = tf.add(tf.multiply(X, W), b)


# %% Loss function will measure the distance between
our observations
# and predictions and average over them.
cost = tf.reduce_sum(tf.pow(Y_pred - Y, 2)) /
(n_observations - 1)


# %% Use gradient descent to optimize W,b
# Performs a single step in the negative gradient
learning_rate = 0.01
optimizer =
tf.train.GradientDescentOptimizer(learning_rate).minimi


# %% We create a session to use the graph
n_epochs = 1000
init = tf.global_variables_initializer()
with tf.Session() as sess:
```

```
    # Here we tell tensorflow that we want to initialize all
    # the variables in the graph so we can use them
    sess.run(init)
    print(xs)
    print(ys)
    # Fit all training data
    prev_training_cost = 0.0
    for epoch_i in range(n_epochs):
        for (x, y) in zip(xs, ys):
            sess.run(optimizer, feed_dict={X: x, Y: y})
        training_cost = sess.run(cost, feed_dict={X: xs, Y: ys})
        curr_W, curr_b = sess.run([W, b])
        print(curr_W, curr_b, training_cost)
        if epoch_i % 20 == 0:
            ax.plot(xs, Y_pred.eval(feed_dict={X:
```

```
xs}, session=sess), 'k', alpha=epoch_i / n_epochs)
                fig.show()
                plt.draw()
            # Allow the training to quit if we've reached a minimum
            if np.abs(prev_training_cost - training_cost) < 0.000001:
                break
            prev_training_cost = training_cost

fig.show()
```

Rechnerprotokoll:

```
parallels@parallels-Parallels-Virtual-Platform:~$ python3
Python 3.6.7 (default, Oct 22 2018, 11:32:17)
[GCC 8.2.0] on linux
Type "help", "copyright", "credits" or "license" for more information.
```

```
>>> # %% imports %matplotlib inline
... import numpy as np
>>> import tensorflow as tf
>>> import matplotlib.pyplot as plt
>>> # %% Let's create some toy data
... plt.ion()
>>> n_observations = 100
>>> fig, ax = plt.subplots(1, 1)
>>> xs = np.linspace(-3, 3, n_observations)
>>> ys = np.sin(xs) + np.random.uniform(-0.5,
0.5, n_observations)
>>> ax.scatter(xs, ys)
<matplotlib.collections.PathCollection object at
0x7f560590bbe0>
>>> fig.show()
>>> plt.draw()
>>> # %% tf.placeholders for the input and output of
the network.
```

```
... # Placeholders are variables which we need to fill
in when we
... # are ready to compute the graph.
... X = tf.placeholder(tf.float32)
>>> Y = tf.placeholder(tf.float32)
>>> # %% We will try to optimize min_(W,b) ||(X*w
+ b) - y||^2
... # The `Variable()` constructor requires an initial
value for the
... # variable,, which can be a `Tensor` of any type
and shape. The
... # initial value defines the type and shape of the
variable.
... # After construction, the type and shape of the
variable are
... # fixed. The value can be changed using one of
the assign methods.
... W = tf.Variable(tf.random_normal([1]),
```

```
name='weight')
>>> b = tf.Variable(tf.random_normal([1]),
name='bias')
>>> Y_pred = tf.add(tf.multiply(X, W), b)
>>>
>>> # %% Loss function will measure the distance
between our observations
... # and predictions and average over them.
... cost = tf.reduce_sum(tf.pow(Y_pred - Y, 2)) /
(n_observations - 1)
>>>
>>> # %% Use gradient descent to optimize W,b
... # Performs a single step in the negative gradient
... learning_rate = 0.01
>>> optimizer =
tf.train.GradientDescentOptimizer(learning_rate).minimi
>>>
>>> # %% We create a session to use the graph
```

```
... n_epochs=1000
>>> init = tf.global_variables_initializer()
>>> with tf.Session() as sess:
...     # Here we tell tensorflow that we want to
initialize all
...     # the variables in the graph so we can use
them
...     sess.run(init)
...     print(xs)
...     print(ys)
...     # Fit all training data
...     prev_training_cost = 0.0
...     for epoch_i in range(n_epochs):
...         for (x, y) in zip(xs, ys):
...             sess.run(optimizer, feed_dict={X:
x, Y: y})
...         training_cost = sess.run(cost,
feed_dict={X: xs, Y: ys})
```

```
...             curr_W, curr_b = sess.run([W, b])
...             print(curr_W, curr_b, training_cost)
...             if epoch_i % 20 == 0:
...                 ax.plot(xs,
Y_pred.eval(feed_dict={X: xs}, session=sess), 'k',
alpha=epoch_i / n_epochs)
...                 fig.show()
...                 plt.draw()
...             # Allow the training to quit if we've
reached a minimum
...             if np.abs(prev_training_cost -
training_cost) < 0.000001:
...                 break
...             prev_training_cost = training_cost
...
# 100 x-Daten
[-3.          -2.93939394 -2.87878788
-2.81818182 -2.75757576 -2.6969697
```

-2.63636364 -2.57575758 -2.51515152

-2.45454545 -2.39393939 -2.33333333

-2.27272727 -2.21212121 -2.15151515

-2.09090909 -2.03030303 -1.96969697

-1.90909091 -1.84848485 -1.78787879

-1.72727273 -1.66666667 -1.60606061

-1.54545455 -1.48484848 -1.42424242

-1.36363636 -1.3030303 -1.24242424

-1.18181818 -1.12121212 -1.06060606 -1.

-0.93939394 -0.87878788

-0.81818182 -0.75757576 -0.6969697

-0.63636364 -0.57575758 -0.51515152

-0.45454545 -0.39393939 -0.33333333

-0.27272727 -0.21212121 -0.15151515

-0.09090909 -0.03030303 0.03030303

0.09090909 0.15151515 0.21212121

0.27272727 0.33333333 0.39393939

0.45454545 0.51515152 0.57575758

```
  0.63636364  0.6969697   0.75757576
0.81818182  0.87878788  0.93939394
  1.          1.06060606  1.12121212
1.18181818  1.24242424  1.3030303
  1.36363636  1.42424242  1.48484848
1.54545455  1.60606061  1.66666667
  1.72727273  1.78787879  1.84848485
1.90909091  1.96969697  2.03030303
  2.09090909  2.15151515  2.21212121
2.27272727  2.33333333  2.39393939
  2.45454545  2.51515152  2.57575758
2.63636364  2.6969697   2.75757576
  2.81818182  2.87878788  2.93939394  3.
  ]
# 100 y-Daten:
[ 0.20291621 -0.22118012 -0.62833878
0.01444744 -0.27653231 -0.81966122
 -0.59394983 -0.68889316 -0.89094116
```

-0.64222339 -0.36528585 -0.31661621

-0.37948344 -0.33735615 -1.06720325

-1.21275391 -0.71440054 -0.89515028

-0.56801334 -0.98468848 -0.54954994

-1.0945503 -1.33175895 -1.34249212

-0.65011852 -0.78674601 -1.35303092

-1.19645055 -1.1630676 -1.14722283

-1.0047393 -1.1928673 -0.88925636

-0.95923765 -0.46293165 -1.2023979

-0.62926533 -0.19748193 -1.05230669

-0.74460138 -0.8929727 -0.08115272

-0.24367908 -0.39987265 0.06714758

-0.05671209 -0.27908047 -0.63617708

-0.30698586 -0.21597079 -0.03565833

-0.27975359 -0.24541802 0.45953916

0.09202181 0.45763097 0.57728143

0.06150595 0.40199538 0.66282468

0.16705133 1.06981763 0.31727183

```
0.29093523  0.48856133  0.33590649
  0.73689616  0.68987514  0.48259013
1.08477711  0.84286125  1.20258011
  0.55556689  1.39794857  1.03707338
0.8518561   1.0564094   0.56761776
  0.53057936  0.55085757  1.28483505
1.35616653  0.85892314  0.53569456
  0.3758622   1.02227012  0.80742031
0.72057286  1.15398355  0.71426198
  0.36634298  1.02687661  0.92441443
0.51944523  0.91051877  0.59040157
  0.32209332 -0.01796203  0.53824307
0.02899414]
# Iteration mit Plot aller 20 Schritte
[-1.4935356] [-0.13225833] 10.572385
[<matplotlib.lines.Line2D object at 0x7f904511cb70>]
[-1.3838066] [-0.13055438] 9.36893
[-1.2806613] [-0.12886626] 8.30555
```

[-1.1837045] [-0.12719482] 7.3659387

[-1.0925653] [-0.12554075] 6.535692

[-1.0068941] [-0.12390465] 5.802076

[-0.9263632] [-0.12228709] 5.153846

[-0.8506643] [-0.12068851] 4.581062

[-0.779507] [-0.11910937] 4.074939

[-0.71261907] [-0.11755012] 3.6277204

[-0.6497446] [-0.11601089] 3.2325506

[-0.5906425] [-0.11449206] 2.88337

[-0.53508717] [-0.11299378] 2.5748284

[-0.48286477] [-0.11151634] 2.30219

[-0.43377584] [-0.11005974] 2.0612786

[-0.3876326] [-0.10862413] 1.848402

[-0.3442579] [-0.1072096] 1.6602951

[-0.30348572] [-0.10581618] 1.4940751

[-0.26516014] [-0.10444393] 1.3471955

[-0.22913408] [-0.10309275] 1.2174037

[-0.19526978] [-0.10176254] 1.1027118

```
[<matplotlib.lines.Line2D object at 0x7f904513da58>]
[-0.1634373] [-0.10045338] 1.0013614
[-0.13351497] [-0.09916513] 0.9118
[-0.10538808] [-0.09789774] 0.83265585
[-0.07894888] [-0.09665104] 0.7627159
[-0.05409618] [-0.09542488] 0.7009094
[-0.03073477] [-0.09421916] 0.64628947
[-0.00877515] [-0.09303365] 0.5980197
[0.01186677] [-0.09186824] 0.55536115
[0.03127005] [-0.09072271] 0.5176608
[0.04950902] [-0.08959687] 0.48434162
[0.06665351] [-0.08849053] 0.4548939
[0.08276922] [-0.08740351] 0.42886704
[0.09791785] [-0.08633552] 0.40586302
[0.11215741] [-0.08528641] 0.38553023
[0.12554248] [-0.08425587] 0.36755776
[0.13812433] [-0.0832438] 0.35167104
[0.14995112] [-0.0822499] 0.33762753
```

[0.16106822] [-0.08127388] 0.32521266

[0.17151816] [-0.08031559] 0.31423715

[0.18134099] [-0.07937472] 0.3045336

[<matplotlib.lines.Line2D object at 0x7f90450b9048>]

[0.19057424] [-0.07845104] 0.2959541

[0.1992534] [-0.07754428] 0.28836796

[0.20741177] [-0.07665425] 0.28165957

[0.21508048] [-0.07578067] 0.275727

[0.22228895] [-0.07492331] 0.2704801

[0.22906479] [-0.0740819] 0.26583925

[0.23543398] [-0.07325623] 0.26173386

[0.24142094] [-0.072446] 0.2581019

[0.24704853] [-0.07165099] 0.25488836

[0.25233835] [-0.07087094] 0.25204465

[0.2573106] [-0.07010563] 0.24952786

[0.2619844] [-0.06935482] 0.24730006

[0.26637772] [-0.06861825] 0.24532771

[0.27050734] [-0.0678957] 0.24358118

```
[0.27438903] [-0.06718691] 0.24203433
[0.27803776] [-0.06649162] 0.24066404
[0.2814674] [-0.06580967] 0.23944986
[0.28469115] [-0.06514079] 0.23837371
[0.28772154] [-0.06448473] 0.2374196
[0.29056993] [-0.06384134] 0.23657347
[<matplotlib.lines.Line2D object at 0x7f90450bb128>]
[0.2932472] [-0.06321033] 0.23582289
[0.29576373] [-0.06259151] 0.23515676
[0.2981294] [-0.06198462] 0.23456533
[0.300353] [-0.06138948] 0.23404005
[0.3024431] [-0.06080589] 0.23357327
[0.30440748] [-0.06023363] 0.23315836
[0.30625394] [-0.05967252] 0.23278928
[0.30798975] [-0.05912232] 0.23246075
[0.30962116] [-0.05858284] 0.23216821
[0.3111545] [-0.0580539] 0.2319075
[0.3125959] [-0.05753528] 0.23167498
```

```
[0.31395072] [-0.05702679] 0.23146749

[0.31522417] [-0.05652824] 0.23128211

[0.3164212] [-0.05603946] 0.23111638

[0.31754622] [-0.05556026] 0.2309681

[0.31860372] [-0.05509046] 0.23083527

[0.31959772] [-0.05462988] 0.23071612

[0.32053193] [-0.05417835] 0.23060918

[0.32141] [-0.0537357] 0.23051307

[0.3222354] [-0.05330175] 0.23042655

[<matplotlib.lines.Line2D object at 0x7f90450bb470>]

[0.32301128] [-0.05287637] 0.2303486

[0.3237405] [-0.05245934] 0.23027825

[0.32442594] [-0.05205055] 0.23021467

[0.32507002] [-0.05164982] 0.23015712

[0.32567558] [-0.05125701] 0.23010492

[0.32624465] [-0.05087192] 0.23005757

[0.3267793] [-0.05049448] 0.23001446

[0.32728192] [-0.05012447] 0.22997521
```

```
[0.3277544] [-0.04976181] 0.22993937

[0.3281983] [-0.04940633] 0.2299066

[0.32861575] [-0.04905788] 0.22987656

[0.3290082] [-0.04871632] 0.22984898

[0.32937708] [-0.04838153] 0.22982359

[0.32972354] [-0.04805339] 0.2298002

[0.33004913] [-0.04773178] 0.22977862

[0.33035526] [-0.04741653] 0.22975864

[0.33064303] [-0.04710753] 0.22974013

[0.33091354] [-0.04680462] 0.22972289

[0.3311676] [-0.04650777] 0.22970688

[0.33140635] [-0.04621683] 0.22969195

[<matplotlib.lines.Line2D object at 0x7f90450c0198>]

[0.3316306] [-0.04593166] 0.22967803

[0.33184144] [-0.04565217] 0.22966497

[0.3320396] [-0.04537822] 0.22965272

[0.3322259] [-0.04510972] 0.22964121

[0.33240113] [-0.04484659] 0.2296304
```

```
[0.33256567] [-0.04458867] 0.22962023

[0.33272025] [-0.04433587] 0.22961059

[0.33286542] [-0.04408811] 0.2296015

[0.33300197] [-0.04384529] 0.22959289

[0.33313015] [-0.04360731] 0.22958477

[0.3332506] [-0.04337407] 0.22957702

[0.33336368] [-0.04314548] 0.22956967

[0.33347008] [-0.04292142] 0.22956267

[0.33357018] [-0.04270184] 0.229556

[0.33366412] [-0.04248665] 0.22954965

[0.33375254] [-0.04227573] 0.2295436

[0.33383548] [-0.04206905] 0.22953781

[0.3339135] [-0.04186647] 0.22953229

[0.33398664] [-0.04166792] 0.229527

[0.3340553] [-0.04147331] 0.22952192

[<matplotlib.lines.Line2D object at 0x7f90450c31d0>]

[0.3341199] [-0.04128261] 0.22951706

[0.33418056] [-0.04109569] 0.2295124
```

[0.33423772] [-0.04091252] 0.22950795

[0.33429137] [-0.040733] 0.22950365

[0.3343417] [-0.04055704] 0.22949953

[0.334389] [-0.04038462] 0.22949556

[0.33443338] [-0.04021563] 0.22949179

[0.3344751] [-0.04005002] 0.22948812

[0.33451432] [-0.03988773] 0.22948457

[0.334551] [-0.03972868] 0.2294812

[0.3345856] [-0.03957277] 0.22947793

[0.3346181] [-0.03941998] 0.22947481

[0.33464855] [-0.03927026] 0.22947179

[0.3346773] [-0.03912352] 0.22946885

[0.33470413] [-0.03897971] 0.22946607

[0.3347294] [-0.03883879] 0.22946331

[0.33475336] [-0.03870068] 0.2294607

[0.3347759] [-0.03856531] 0.22945818

[0.33479688] [-0.03843268] 0.22945575

[0.33481655] [-0.03830269] 0.22945338

```
[<matplotlib.lines.Line2D object at 0x7f90450c5198>]

[0.3348351] [-0.03817529] 0.22945113

[0.33485246] [-0.03805044] 0.22944891

[0.3348689] [-0.03792807] 0.2294468

[0.33488408] [-0.03780816] 0.22944477

[0.3348983] [-0.03769065] 0.22944279

[0.33491185] [-0.03757549] 0.2294409

[0.33492458] [-0.03746263] 0.22943905

[0.33493653] [-0.03735201] 0.22943726

[0.3349477] [-0.0372436] 0.22943555

[0.3349582] [-0.03713737] 0.22943386

[0.33496794] [-0.03703327] 0.22943226

[0.33497703] [-0.03693125] 0.22943069

[0.3349856] [-0.03683123] 0.2294292

[0.33499357] [-0.03673325] 0.22942773

[0.33500117] [-0.03663723] 0.22942631

[0.3350081] [-0.03654309] 0.22942497

[0.33501482] [-0.03645087] 0.22942366
```

```
[0.33502105] [-0.03636049] 0.22942236

[0.33502698] [-0.03627193] 0.22942114

[0.3350325] [-0.03618513] 0.22941992

[<matplotlib.lines.Line2D object at 0x7f90450c5550>]

[0.33503768] [-0.03610006] 0.22941877

[0.33504245] [-0.03601667] 0.22941762

[0.3350471] [-0.03593496] 0.22941655

[0.33505127] [-0.03585487] 0.2294155

[0.33505526] [-0.0357764] 0.2294145

[0.33505905] [-0.03569948] 0.22941352

>>> fig.show()
```

====================================

mit ClassPad:

xs:=seq(x, x, -3, 3, $\frac{6}{99}$)

{-3,-2.939393939,-2.878787879,-2.818181818,-

approx(ans)

{-3,-2.939393939,-2.878787879,-2.818181818,-

ys:=sin(xs)+randList(100)-0.5

{0.01382481814,-0.6697871794,-0.4807604983,-

approx(ans)

{0.01382481814,-0.6697871794,-0.4807604983,-

STAT-Menü

y1(x)

0.1221540342•sin(3.591295599•x-0.5414384286)-0

sum((y1(xs)-ys)^2)/99

0.6395667985

Daten von Tensorflow,

yss:={-0.18295909, 0.11708618, -0.40319602,

{-0.18295909,0.11708618,-0.40319602,-0.79582

LinearReg xs,yss,1,y2

done

DispStat

done

===================

Lineare Regression

y=a*x+b

a = 0.3555142

b = -9.113E-3

r = 0.7722933

r^2 = 0.5964369

MSe = 0.2670806

===================

cost = 0.26442605

0.26442605*99/98

0.267124275

stop

Anlage:

Bild mit verrauschten Daten bei linearer Regression

Download für dieses Dokument:

www.informatik.htw-dresden.de/
~paditz/Tensorflow-Ue13.pdf

Zusatz:

sin-Regression:

=============

```
xs:=seq(x,x,-3,3,6/99)
     {-3,-2.939393939,-2.878787879,-2.818181818,-▶
ys:=sin(xs)+randList(100)-0.5
     {-0.2310886776,0.2671283261,-0.5656227723,0.▶

LinearReg xs,ys,1,y1,On
                                                    done
y1(x)
                          0.335014124•x+1.168330812E-3
MSe
                                            0.2823086501
sum((ys-y1(xs))^2)/98
                                            0.2823086501
sum((residual)^2)/98
                                            0.2823086501
```

==================

```
SinReg xs,ys,y2,On
                                                    done
```

y2(x)

0.09696177937·sin(6.551170793·x+2.375239149)-1▶

DispStat

done

=====================

Sinus-Reg. mit ClassPad

y=a·sin(b·x+c)+d

aCoef

0.09696177937

bCoef

6.551170793

cCoef

2.375239149

dCoef

-1.705322392E-3

MSe

0.6280404286

sum((ys-y2(xs))^2)/98

0.6280404286

sum((residual)^2)/98

0.6280404286

unbrauchbares Ergebnis!

=====================

stop

STAT-Menü

Levenberg-Marquardt-Verfahren:

(als ClassPad-Programm im library-Ordner)

```
DelVar a,b,c,d
                                                        done
SinDReg(xs,ys,1.,1.,0,-.5,1,10)
                                                        done
vecab
                                          [0.9845803391   ]
                                          [0.9775726083   ]
                                          [0.01661479831  ]
                                          [-0.02063880012 ]
vecs
                                          [5.520763474E-15 ]
                                          [-2.964031247E-16]
                                          [1.859443018E-17 ]
                                          [-1.180075306E-17]
MSerr
                                                0.0684881385
DelVar a,b,c,d
                                                        done
{a=vecab[1,1],b=vecab[2,1],c=vecab[3,1],d=vecab|▶
    {a=0.9845803391,b=0.9775726083,c=0.016614798:▶
Define y3(x)=a•sin(b•x+c)+d|{a=0.9932587591,b=1.▶
                                                        done
y3(x)
    0.9932587591•sin(1.013914946•x+0.08034471995)+▶
Define y3(x)=0.9932587591•sin(1.013914946•x+0.0:▶
                                                        done
sum((ys-y3(xs))^2)/98
                                               0.07325179357
```

sin-Regression mit Tensorflow:

```
=============================
python3
# %% imports %matplotlib inline

import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
# %% Let's create some toy data

plt.ion()
n_observations = 100
fig, ax = plt.subplots(1, 1)
xs = np.linspace(-3, 3, n_observations)
ys = np.sin(xs) + np.random.uniform(-0.5, 0.5,
n_observations)
ax.scatter(xs, ys)
fig.show()
plt.draw()
# %% tf.placeholders for the input and output of the
network.
# Placeholders are variables which we need to fill in
when we
# are ready to compute the graph.

X = tf.placeholder(tf.float32)
Y = tf.placeholder(tf.float32)
# %% We will try to optimize min_(W,b)
||(a*sin(X*b + c)+d - y||^2
# The `Variable()` constructor requires an initial value
```

```
for the
# variable,, which can be a `Tensor` of any type and
shape. The
# initial value defines the type and shape of the
variable.
# After construction, the type and shape of the
variable are
# fixed. The value can be changed using one of the
assign methods.

a = tf.Variable(tf.random_normal([1]),
name='weight_a')
b = tf.Variable(tf.random_normal([1]),
name='weight_b')
c = tf.Variable(tf.random_normal([1]),
name='bias_c')
d = tf.Variable(tf.random_normal([1]),
name='bias_d')

Y_pred = tf.add(tf.sin(tf.add(tf.multiply(X,
b),c)), d)

# %% Loss function will measure the distance between
our observations
# and predictions and average over them.

cost = tf.reduce_sum(tf.pow(Y_pred - Y, 2)) /
(n_observations - 2)
```

```
# %% Use gradient descent to optimize a,b,c,d
# Performs a single step in the negative gradient

learning_rate = 0.01
optimizer =
tf.train.GradientDescentOptimizer(learning_rate).minimi▶

# %% We create a session to use the graph

n_epochs = 1000
init = tf.global_variables_initializer()
with tf.Session() as sess:
    # Here we tell tensorflow that we want to initialize
all
    # the variables in the graph so we can use them
    sess.run(init)
    print(sess.run([a,b,c,d]))
    print(xs)
    print(ys)
    # Fit all training data
    prev_training_cost = 0.0
    for epoch_i in range(n_epochs):
        for (x, y) in zip(xs, ys):
            sess.run(optimizer, feed_dict={X: x, Y:
y})
        training_cost = sess.run(cost, feed_dict={X:
xs, Y: ys})
        curr_a, curr_b, curr_c, curr_d =
sess.run([a,b,c,d])
```

```
        print(curr_a, curr_b, curr_c, curr_d,
training_cost)
        if epoch_i % 100 == 0:
            ax.plot(xs, Y_pred.eval(feed_dict={X:
xs}, session=sess), 'k', alpha=epoch_i / n_epochs)
            fig.show()
            plt.draw()
        # Allow the training to quit if we've reached
a minimum
        if np.abs(prev_training_cost - training_cost)
< 0.000001:
            break
        prev_training_cost = training_cost

fig.show()
```

Rechnerprotokoll:

===============

```
parallels@parallels-Parallels-Virtual-Platform:~$ python3
Python 3.6.7 (default, Oct 22 2018, 11:32:17)
[GCC 8.2.0] on linux
Type "help", "copyright", "credits" or "license" for
more information.
>>> # %% imports %matplotlib inline
...
>>> import numpy as np
>>> import tensorflow as tf
>>> import matplotlib.pyplot as plt
>>> # %% Let's create some toy data
```

```
...
>>> plt.ion()
>>> n_observations = 100
>>> fig, ax = plt.subplots(1, 1)
>>> xs = np.linspace(-3, 3, n_observations)
>>> ys = np.sin(xs) + np.random.uniform(-0.5,
0.5, n_observations)
>>> ax.scatter(xs, ys)
<matplotlib.collections.PathCollection object at
0x7feff311ebe0>
>>> fig.show()
>>> plt.draw()
>>> # %% tf.placeholders for the input and output of
the network.
... # Placeholders are variables which we need to fill
in when we
... # are ready to compute the graph.
...
>>> X = tf.placeholder(tf.float32)
>>> Y = tf.placeholder(tf.float32)
>>> # %% We will try to optimize min_(W,b)
||(a*sin(X*b + c)+d - y||^2
... # The `Variable()` constructor requires an initial
value for the
... # variable,, which can be a `Tensor` of any type
and shape. The
... # initial value defines the type and shape of the
variable.
... # After construction, the type and shape of the
```

```
variable are
... # fixed. The value can be changed using one of
the assign methods.
...
>>> a = tf.Variable(tf.random_normal([1]),
name='weight_a')
>>> b = tf.Variable(tf.random_normal([1]),
name='weight_b')
>>> c = tf.Variable(tf.random_normal([1]),
name='bias_c')
>>> d = tf.Variable(tf.random_normal([1]),
name='bias_d')
>>> Y_pred = tf.add(tf.sin(tf.add(tf.multiply(X,
b),c)), d)
>>>
>>> # %% Loss function will measure the distance
between our observations
... # and predictions and average over them.
...
>>> cost = tf.reduce_sum(tf.pow(Y_pred - Y, 2)) /
(n_observations - 2)
>>>
>>> # %% Use gradient descent to optimize a,b,c,d
... # Performs a single step in the negative gradient
...
>>> learning_rate = 0.01
>>> optimizer =
tf.train.GradientDescentOptimizer(learning_rate).minimi
>>>
```

```
>>> # %% We create a session to use the graph
...
>>> n_epochs=1000
>>> init = tf.global_variables_initializer()
>>> with tf.Session() as sess:
...     # Here we tell tensorflow that we want to
initialize all
...     # the variables in the graph so we can use
them
...     sess.run(init)
...     print(xs)
...     print(ys)
...     # Fit all training data
...     prev_training_cost = 0.0
...     for epoch_i in range(n_epochs):
...         for (x, y) in zip(xs, ys):
...             sess.run(optimizer, feed_dict={X:
x, Y: y})
...         training_cost = sess.run(cost,
feed_dict={X: xs, Y: ys})
...         curr_a, curr_b, curr_c, curr_d =
sess.run([a,b,c,d])
...         print(curr_a, curr_b, curr_c, curr_d,
training_cost)
...         if epoch_i % 20 == 0:
...             ax.plot(xs,
Y_pred.eval(feed_dict={X: xs}, session=sess), 'k',
alpha=epoch_i / n_epochs)
...             fig.show()
```

```
...                 plt.draw()
...             # Allow the training to quit if we've
reached a minimum
...             if np.abs(prev_training_cost -
training_cost) < 0.000001:
...                 break
...             prev_training_cost = training_cost
...
[-3.          -2.93939394 -2.87878788
-2.81818182 -2.75757576 -2.6969697
 -2.63636364 -2.57575758 -2.51515152
-2.45454545 -2.39393939 -2.33333333
 -2.27272727 -2.21212121 -2.15151515
-2.09090909 -2.03030303 -1.96969697
 -1.90909091 -1.84848485 -1.78787879
-1.72727273 -1.66666667 -1.60606061
 -1.54545455 -1.48484848 -1.42424242
-1.36363636 -1.3030303  -1.24242424
 -1.18181818 -1.12121212 -1.06060606 -1.
   -0.93939394 -0.87878788
 -0.81818182 -0.75757576 -0.6969697
-0.63636364 -0.57575758 -0.51515152
 -0.45454545 -0.39393939 -0.33333333
-0.27272727 -0.21212121 -0.15151515
 -0.09090909 -0.03030303  0.03030303
0.09090909  0.15151515  0.21212121
  0.27272727  0.33333333  0.39393939
0.45454545  0.51515152  0.57575758
  0.63636364  0.6969697   0.75757576
```

```
0.81818182  0.87878788  0.93939394
  1.          1.06060606  1.12121212
1.18181818  1.24242424  1.3030303
  1.36363636  1.42424242  1.48484848
1.54545455  1.60606061  1.66666667
  1.72727273  1.78787879  1.84848485
1.90909091  1.96969697  2.03030303
  2.09090909  2.15151515  2.21212121
2.27272727  2.33333333  2.39393939
  2.45454545  2.51515152  2.57575758
2.63636364  2.6969697   2.75757576
  2.81818182  2.87878788  2.93939394  3.
  ]
[-0.63384361 -0.36607486  0.0350044
-0.45321797 -0.03325758 -0.83480875
 -0.17922524 -0.97337148 -0.20085492
-0.87569599 -1.08640322 -1.09640202
 -0.7789137  -0.71123747 -1.0860933
-0.69226497 -0.77965481 -0.97976277
 -0.60846786 -0.94568706 -0.89393624
-0.97186363 -0.57957417 -0.71514532
 -1.24489263 -0.89386646 -1.27216058
-1.0654602  -1.36567641 -1.0929979
 -1.09688741 -0.97754024 -1.17212534
-0.93366606 -0.85698759 -0.70966972
 -0.72223662 -0.97807535 -0.41484859
-0.54773967 -0.17252735 -0.8861725
 -0.66196759 -0.54526795 -0.08960642
-0.72607013 -0.69690249 -0.36821527
```

```
 -0.08131653  0.00825096 -0.43569732
-0.24669398 -0.2481128  -0.02082426
 -0.06780346  0.07742522  0.48423279
0.61862695  0.53270218  0.2127406
  0.72054377  0.30615222  0.76446249
0.86144103  1.10519689  0.61675945
  0.76929073  0.71768204  1.04815753
1.01594407  0.46943198  0.83947483
  0.95615742  0.96786794  1.24216731
0.72993708  0.61533662  1.14163974
  0.68052709  0.5800364   1.37301941
0.9004874   1.23238062  1.02134569
  1.13317556  0.4508377   0.71626227
0.36799607  0.50777854  0.55678726
  0.9658721   0.33184332  0.90190796
0.480088    0.75542073  0.84187995
 -0.15390561  0.68946099 -0.20612243
-0.03271348]
[0.9853692] [2.075419] [-1.1137652]
[-1.1549263] 2.3176746
[<matplotlib.lines.Line2D object at 0x7fefef8567f0>]
...
[<matplotlib.lines.Line2D object at 0x7fefec841b00>]
[0.9853692] [0.9874731] [-0.0686608]
[-0.05719525] 0.07072975
[0.9853692] [0.9874767] [-0.06854647]
[-0.05720551] 0.07072843
[0.9853692] [0.9874806] [-0.06843322]
[-0.05721568] 0.070727125
```

```
[0.9853692] [0.9874841] [-0.06832103]
[-0.05722577] 0.070725866
[0.9853692] [0.9874876] [-0.06821001]
[-0.05723577] 0.07072462
[0.9853692] [0.9874913] [-0.06809995]
[-0.05724567] 0.07072339
[0.9853692] [0.98749477] [-0.067991]
[-0.0572555] 0.07072219
[0.9853692] [0.987498] [-0.06788305]
[-0.05726525] 0.070721015
[0.9853692] [0.9875014] [-0.06777614]
[-0.0572749] 0.07071987
[0.9853692] [0.9875046] [-0.06767029]
[-0.05728448] 0.07071873
[0.9853692] [0.98750776] [-0.06756542]
[-0.05729401] 0.07071762
[0.9853692] [0.9875108] [-0.06746153]
[-0.05730342] 0.07071652
[0.9853692] [0.987514] [-0.06735864]
[-0.05731278] 0.07071546
[0.9853692] [0.98751736] [-0.06725676]
[-0.05732203] 0.07071441
[0.9853692] [0.98752075] [-0.06715582]
[-0.05733119] 0.070713386
[0.9853692] [0.98752385] [-0.06705587]
[-0.05734029] 0.07071238
[0.9853692] [0.987527] [-0.06695688]
[-0.05734929] 0.07071139
>>> fig.show()
```

```
>>>
```

LM-Verfahren:

{a=0.9932587591,b=1.013914946,c=0.0803447199

MSerr = 0.0684881385

Tensorflow:

[a=0.9853692] [b=0.987527] [c=-0.06695688]

[d=-0.05734929]

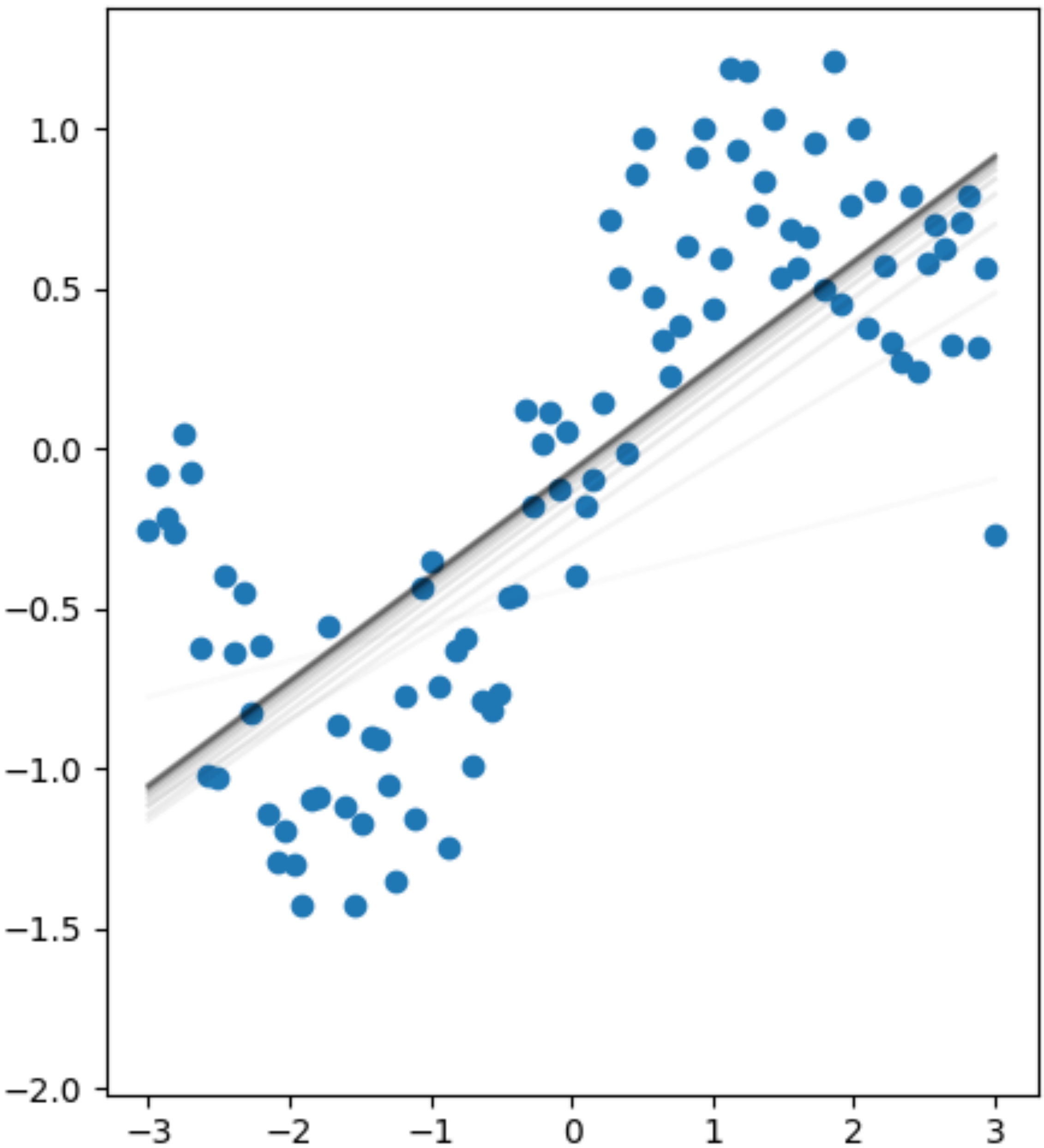
cost = 0.07071139

Download für dieses Dokument:

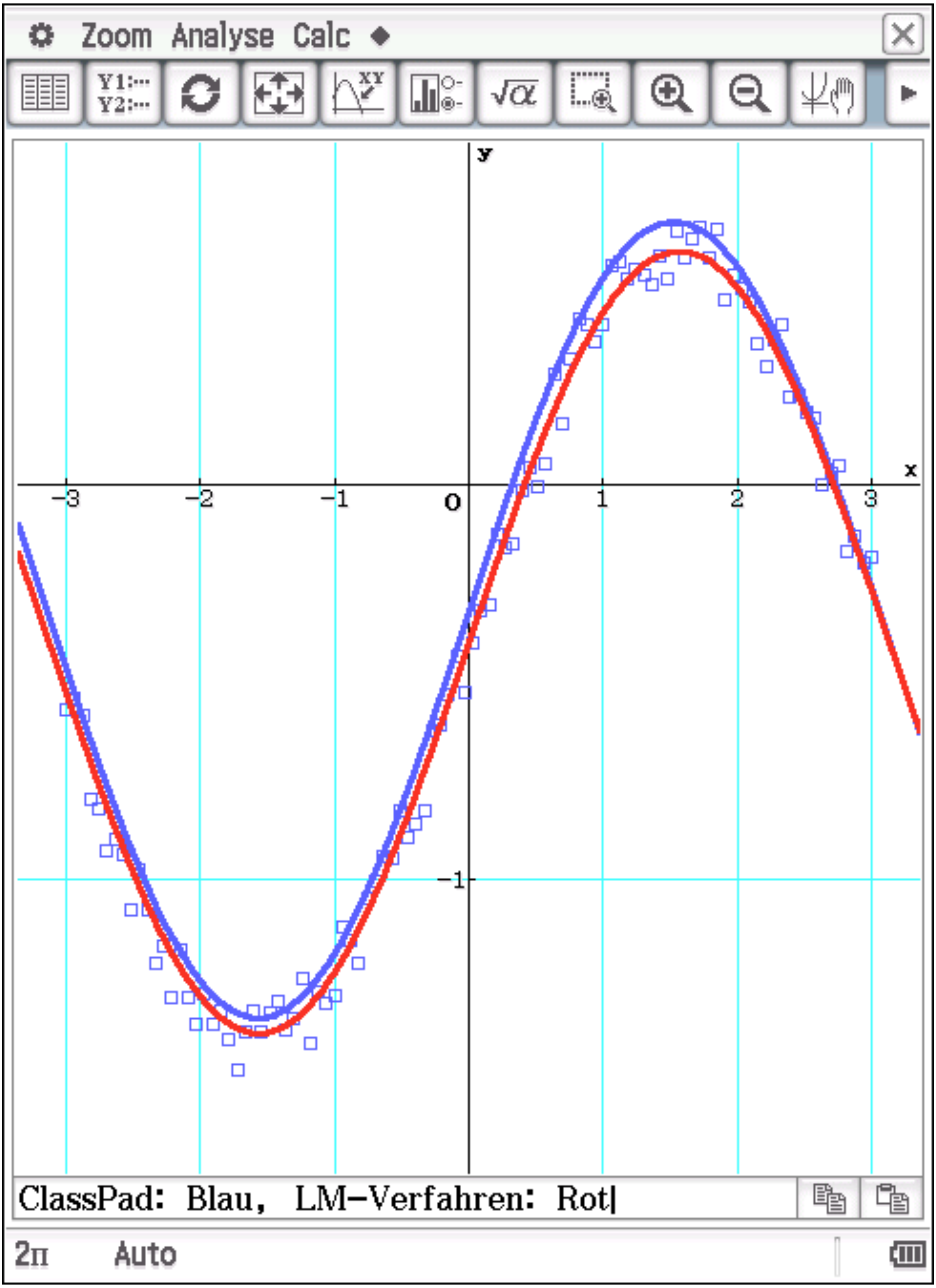
www.informatik.htw-dresden.de/
~paditz/Tensorflow-Ue15.pdf

Lineare Regression mit Tensorflow:

Verrauschte sin-Werte:

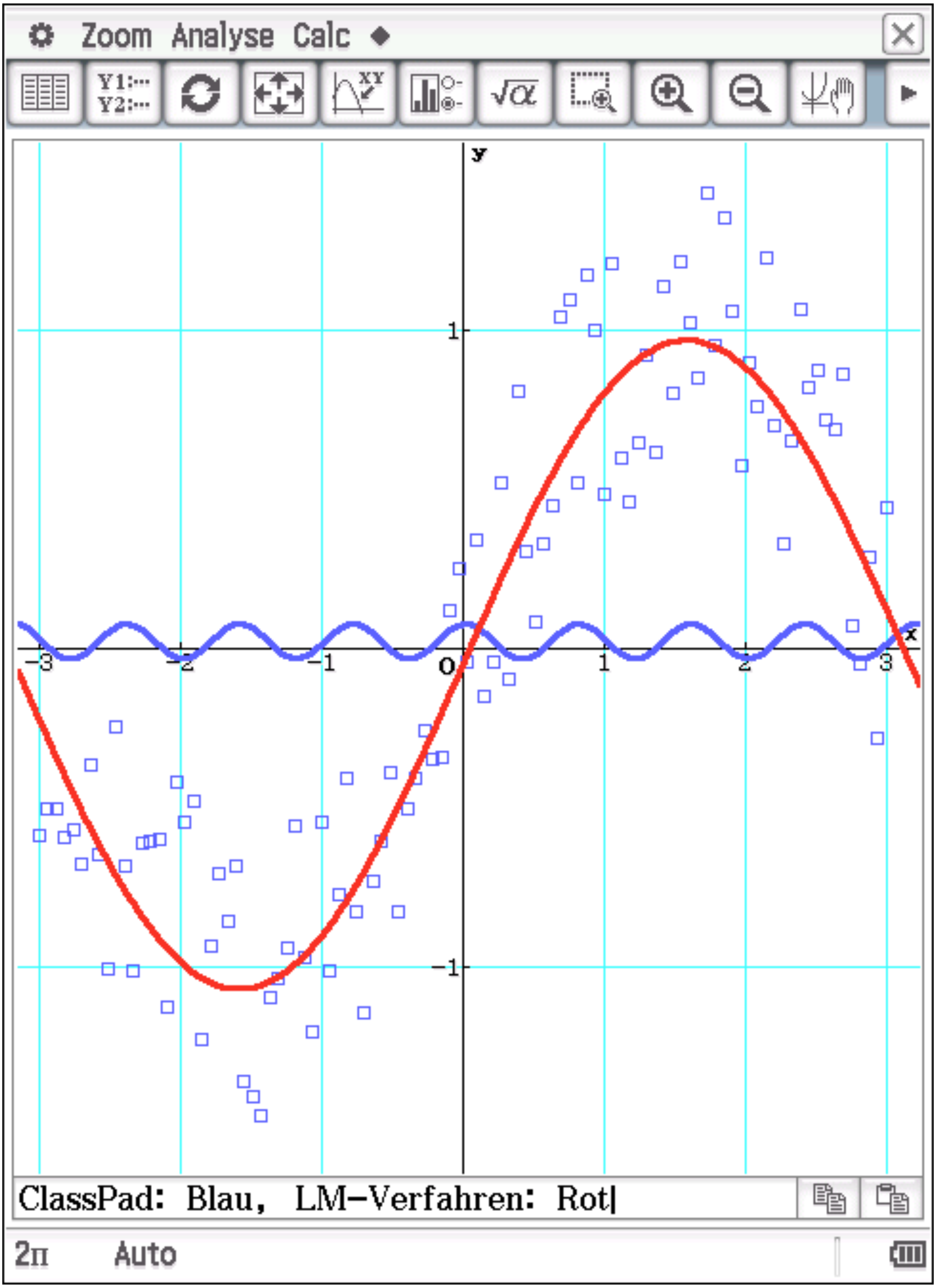


Sin-Regression: schwache Störung der sin-Werte

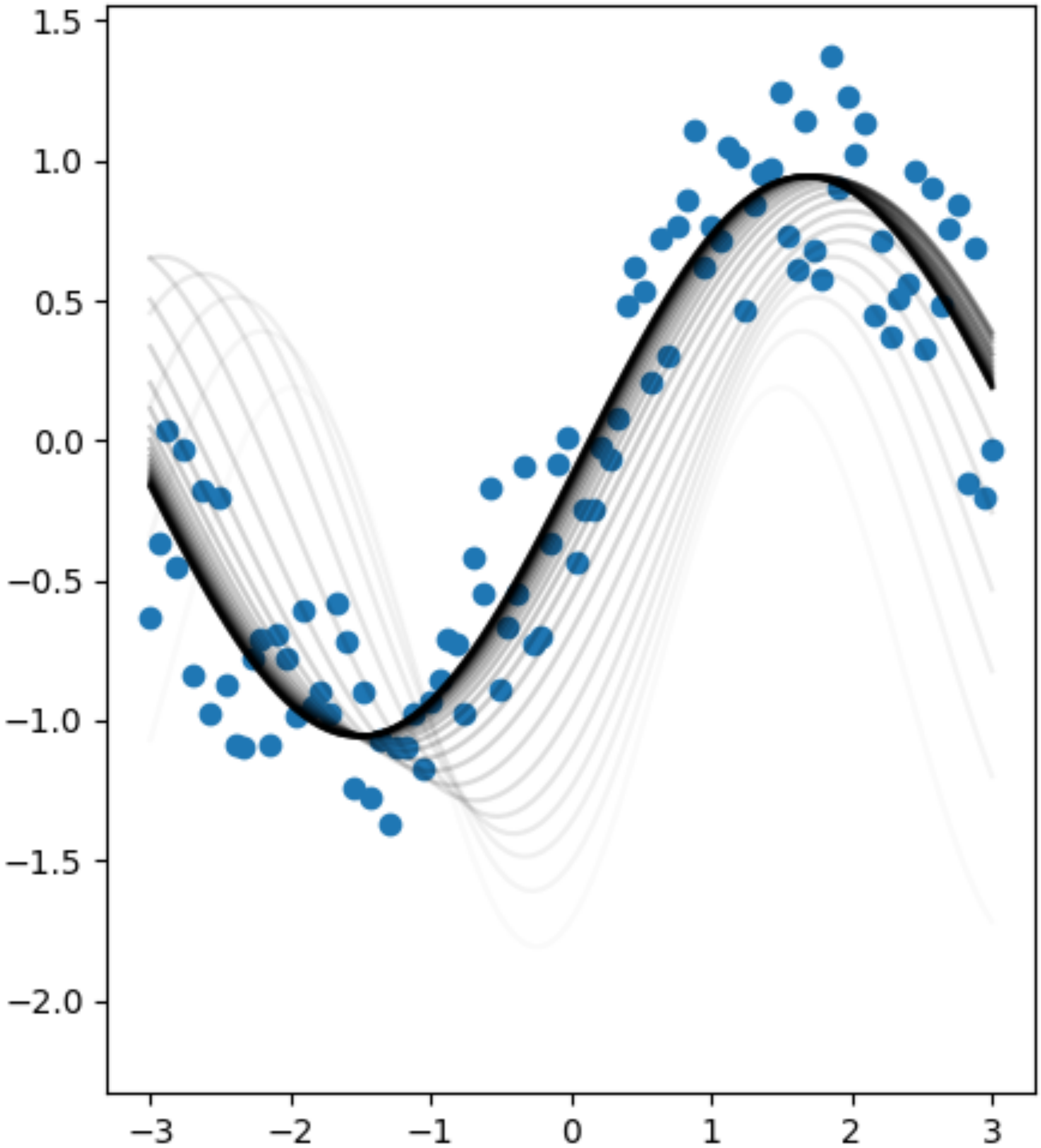


Sin-Regression: starke Störung der sin-Werte, blaue Kurve:

ClassPad versagt hier und liefert ein sinnloses Ergebnis!

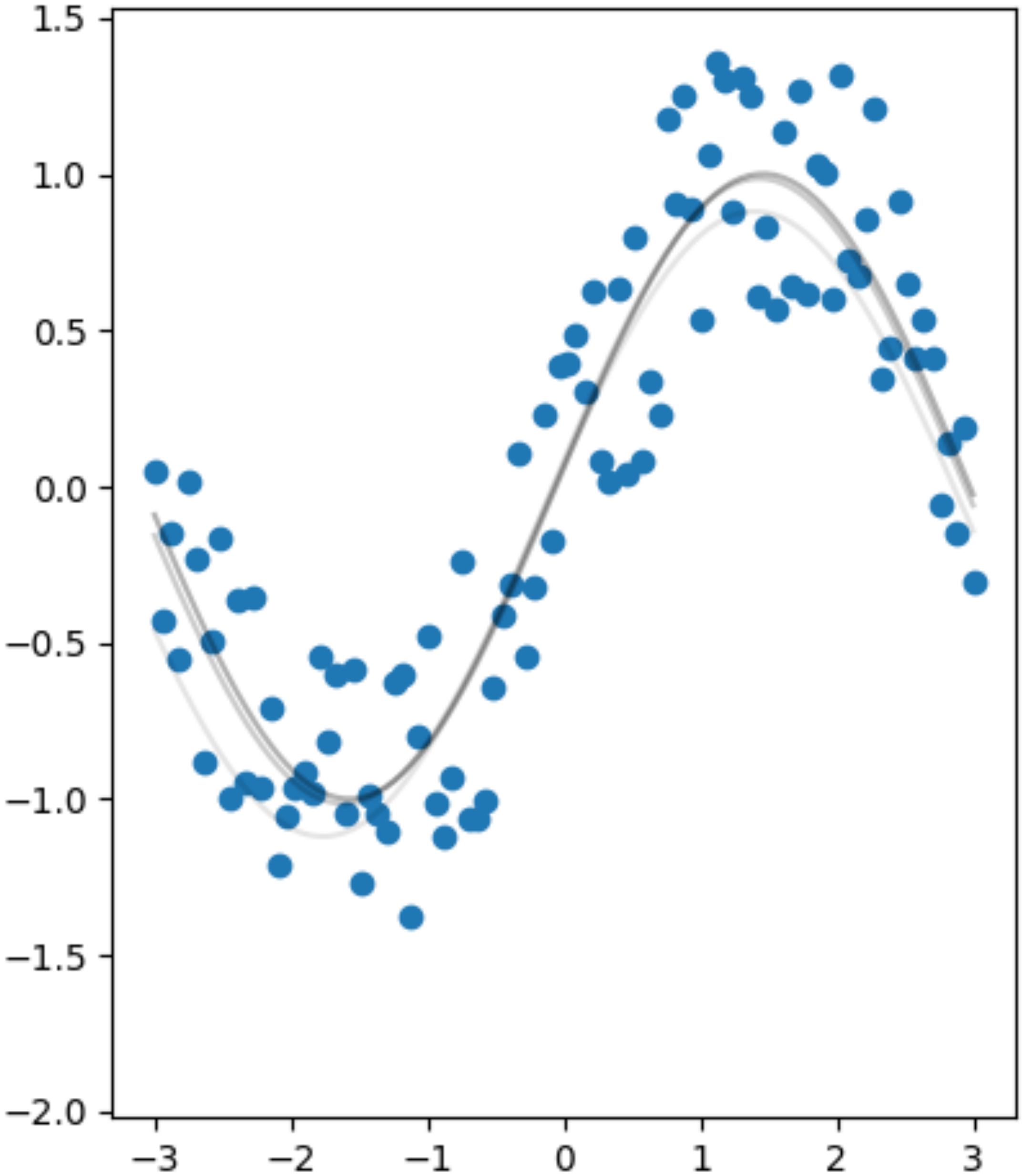


mit Tensorflow:



mit Tensorflow:

erneute Simulation mit anders gestörten Daten



mit Tensorflow:

erneute Simulation mit anders gestörten Daten,

Verfahren konvergiert nicht wie gewünscht