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**Mathematik-Grundlagen als eActivity mit ClassPad**

**lineare Regression in TensorFlow**

**Gradientenverfahren – steilster Abstieg zum Min!**



**Quelle:**

[https://github.com/aymericdamien/TensorFlow-Examples/  
blob/master/examples/2\\_BasicModels/linear\\_regression.py](https://github.com/aymericdamien/TensorFlow-Examples/blob/master/examples/2_BasicModels/linear_regression.py)

s. auch:

<https://github.com/tensorflow/tensorflow/issues/8630>

oder:

<https://stackoverflow.com/questions/43170017/>

**linear-regression-with-tensorflow**

<https://stackoverflow.com/questions/43170017/>

[linear-regression-with-tensorflow/43170585](https://stackoverflow.com/questions/43170017/linear-regression-with-tensorflow/43170585)

und

<https://www.geeksforgeeks.org/introduction-to-tensorflow/>

und

<http://www.machineintelligence.com/linearregression/>

### Suchworte in google.de:

tensorflow "Optimization Finished!" "Training cost= ["  
" [3.3, 4.4, 5.5, 6.71, 6.93, "

train\_X:={3.3, 4.4, 5.5, 6.71, 6.93, 4.168, 9.779, 6.182, 7.5

{3.3, 4.4, 5.5, 6.71, 6.93, 4.168, 9.779, 6.182, 7.5

train\_Y:={1.7, 2.76, 2.09, 3.19, 1.694, 1.573, 3.366, 2.596,

{1.7, 2.76, 2.09, 3.19, 1.694, 1.573, 3.366, 2.596,

STAT-Menü lin. Regression

DelVar W, b

done

X\_liste:=listToMat(train\_X)

```
[ 3.3  
 4.4  
 5.5  
 6.71  
 6.93  
 4.168  
 9.779  
 6.182  
 7.59  
 2.167  
 7.042  
 10.791  
 5.313  
 7.997  
 5.654  
 9.27  
 3.1 ]
```

Y\_liste:=listToMat(train\_Y)

```
[ 1.7  
 2.76  
 2.09  
 3.19  
 1.694  
 1.573  
 3.366  
 2.596  
 2.53  
 1.221  
 2.827  
 3.465  
 1.65  
 2.904  
 2.42  
 2.94  
 1.3 ]
```

**Differenzvektor:**

D\_liste:=Y\_liste-W\*X\_liste-b\*fill(1,17,1)

$$\begin{bmatrix} -3.3 \cdot W - b + 1.7 \\ -4.4 \cdot W - b + 2.76 \\ -5.5 \cdot W - b + 2.09 \\ -6.71 \cdot W - b + 3.19 \\ -6.93 \cdot W - b + 1.694 \\ -4.168 \cdot W - b + 1.573 \\ -9.779 \cdot W - b + 3.366 \\ -6.182 \cdot W - b + 2.596 \\ -7.59 \cdot W - b + 2.53 \\ -2.167 \cdot W - b + 1.221 \\ -7.042 \cdot W - b + 2.827 \\ -10.791 \cdot W - b + 3.465 \\ -5.313 \cdot W - b + 1.65 \\ -7.997 \cdot W - b + 2.904 \\ -5.654 \cdot W - b + 2.42 \\ -9.27 \cdot W - b + 2.94 \\ -3.1 \cdot W - b + 1.3 \end{bmatrix}$$

**algebraische Lösung:** Orthogonalitätsbedingungen:

dotP(D\_liste, X\_liste)=0

$$-2.167 \cdot (2.167 \cdot W + b - 1.221) - 3.1 \cdot (3.1 \cdot W + b - 1.3) - 4. \quad \blacktriangleright$$

Equ1:=expand(ans)

$$-752.797217 \cdot W - 105.893 \cdot b + 274.017544 = 0$$

dotP(D\_liste, fill(1,17,1))=0

$$-105.893 \cdot W - 17 \cdot b + 40.226 = 0$$

Equ2:=ans

$$-105.893 \cdot W - 17 \cdot b + 40.226 = 0$$

$$\begin{cases} \text{Equ1} \\ \text{Equ2} \end{cases} \Big|_{W, b}$$

$$\{W=0.2516349443, b=0.7988012262\}$$

## Lineare Regression:

=====

LinearReg train\_X, train\_Y, 1, y10

done

DispStat

done

y10(x)

0.2516349443·x+0.7988012262

stop

=====

Lineare Regression

y=a\*x+b

a = 0.2516349

b = 0.7988012

r = 0.8323918

r<sup>2</sup> = 0.692876

MSe = 0.174372

=====

**analytische Lösung:**  $\text{grad}(\text{cost}(W, b)) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

dotP(D\_liste, D\_liste) / dim(train\_X)

0.05882352941 · ((10.791 · W + b - 3.465)<sup>2</sup> + (9.779 · W +

expand(ans)

44.28218924 · W<sup>2</sup> + b<sup>2</sup> + 12.458 · W · b - 32.23735812 · W - 4

Define cost(W, b) = 44.28218924 · W<sup>2</sup> + b<sup>2</sup> + 12.458 · W · b -

done

$$\begin{cases} \frac{d}{dW}(\text{cost}(W, b)) = 0 \\ \frac{d}{db}(\text{cost}(W, b)) = 0 \end{cases} \Big|_{W, b}$$

{W=0.2516349444, b=0.7988012252}

Define z1(x, y)=cost(x, y)

done

stop

3D-Grafik Z1: ...  
Z2: ...

solve(s=cost(W, b), b)

$$\{b = -3.223775793E-28 \cdot (1.932206332E+28 \cdot W - 941429) \}$$

expand(ans)

$$\{b = -6.229 \cdot W + 3.034957485E-19 \cdot (-5.951327671E+37) \}$$

getRight(ans)

$$\{-6.229 \cdot W + 1.720568677E-25 \cdot (-1.763926965E+24) \}$$

listToMat(ans)

$$\begin{bmatrix} -6.229 \cdot W + 1.720568677E-25 \cdot (-1.763926965E+24) \\ -6.229 \cdot W - 1.720568677E-25 \cdot (-1.763926965E+24) \end{bmatrix}$$

ans[2, 1]

$$-6.229 \cdot W - 1.720568677E-25 \cdot (-1.763926965E+24) \cdot (1.720568677E-25)$$

$$-6.229 \cdot W - (-1.763926965E+24 \cdot (1.720568677E-25))^2$$

$$-6.229 \cdot W - (-5.221852784E-26 \cdot (1.049770736E+26 \cdot W - 5.221852784E-26))$$

$$-6.229 \cdot W - (-(1.049770736E+26 \cdot 5.221852784E-26 \cdot W - 5.221852784E-26))$$

$$-6.229 \cdot W - (-5.48174824 \cdot W^2 + 2.758798826 \cdot W + 0.998798826)$$

**Definition von Höhenlinien der cost-Funktion:**

$x=t, y=W, z=cost(W, b)$

Define xst2(s, t)=t

done

Define yst2(s, t)=-6.229\*t+(-5.48174824\*t<sup>2</sup>+2.7587

done

Define zst2(s, t)=s

done

Define xst3(s, t)=t

done

Define yst3(s, t)=-6.229\*t+(-5.48174824\*t<sup>2</sup>+2.7587

done

Define zst3(s, t)=s

done

stop

3D-Grafik Z1:...  
Z2:...

2D-Grafik Höhenlinien Y1:...  
Y2:...

**1. Iteration mit tensorflow:**

=====

Startwerte per Zufall ausgewählt: W= [0.38903466]

b= [-0.40474084]

Epoch: 0000 cost= 0.177051708 W= [0.39435494]

b= [-0.3878391]

Epoch: 0001 cost= 0.174632162 W= [0.39232808]  
b= [-0.37236074]  
Epoch: 0002 cost= 0.172295541 W= [0.39030755]  
b= [-0.35708445]  
Epoch: 0003 cost= 0.170018047 W= [0.38831297]  
b= [-0.34200448]  
Epoch: 0004 cost= 0.167798087 W= [0.38634402]  
b= [-0.32711828]  
Epoch: 0005 cost= 0.165634304 W= [0.38440034]  
b= [-0.31242332]  
Epoch: 0006 cost= 0.163525149 W= [0.38248163]  
b= [-0.29791716]  
Epoch: 0007 cost= 0.161469370 W= [0.38058755]  
b= [-0.2835974]  
Epoch: 0008 cost= 0.159465447 W= [0.37871787]  
b= [-0.2694616]  
Epoch: 0009 cost= 0.157512143 W= [0.37687218]  
b= [-0.25550747]

W:={0.38903466, 0.39435494, 0.39232808, 0.39030755} ▶  
{0.38903466, 0.39435494, 0.39232808, 0.39030755} ▶

dim(ans)

11

b:={-0.40474084, -0.3878391, -0.37236074, -0.35708445} ▶  
{-0.40474084, -0.3878391, -0.37236074, -0.35708445} ▶

dim(ans)

11


## 2. Iteration mit tensorflow:

=====



Startwerte per Zufall ausgewählt: W= [-0.6830545]  
b= [1.1212226]  
Epoch: 0000 cost= 0.093539596 W= [0.17438477]  
b= [1.257438]  
Epoch: 0010 cost= 0.089693040 W= [0.18378624]  
b= [1.2042997]  
Epoch: 0020 cost= 0.087661669 W= [0.1900068] b=  
[1.1572697]  
Epoch: 0030 cost= 0.086108372 W= [0.19547294]  
b= [1.1159436]  
Epoch: 0040 cost= 0.084922418 W= [0.20027587]  
b= [1.0796316]  
Epoch: 0050 cost= 0.084018461 W= [0.20449626]  
b= [1.0477235]  
Epoch: 0060 cost= 0.083330818 W= [0.2082046] b=  
[1.019687]  
Epoch: 0070 cost= 0.082808919 W= [0.21146306]  
b= [0.99505186]  
Epoch: 0080 cost= 0.082413912 W= [0.21432634]  
b= [0.9734042]  
Epoch: 0090 cost= 0.082115903 W= [0.21684231]  
b= [0.9543826]  
Optimization Finished!  
Training cost= [0.08191158] W= [0.21884456] b=  
[0.9392446]

W1:={-0.6830545, 0.17438477, 0.18378624, 0.1900068, 0.19547294, 0.20027587, 0.20449626, 0.2082046, 0.21146306, 0.21432634, 0.21684231, 0.21884456}  
b1:={1.1212226, 1.257438, 1.2042997, 1.1572697, 1.1159436, 1.0796316, 1.0477235, 1.019687, 0.99505186, 0.9734042, 0.9543826, 0.9392446}

{1.1212226, 1.257438, 1.2042997, 1.1572697, 1.11 

$\dim(W1)=\dim(b1)$

11=11

### 3. Iteration mit tensorflow:

=====

Startwerte per Zufall ausgewählt: W= [0.16528997]

b= [-0.08805541]

Epoch: 0000 cost= 0.529334068 W= [0.22420149]

b= [0.020639995]

Epoch: 0001 cost= 0.500386834 W= [0.21591327]

b= [0.10483948]

Epoch: 0002 cost= 0.475245655 W= [0.20835607]

b= [0.1816125]

Epoch: 0003 cost= 0.453363746 W= [0.2014654] b=

[0.25161412]

Epoch: 0004 cost= 0.434277445 W= [0.19518256]

b= [0.31544152]

Epoch: 0005 cost= 0.417595029 W= [0.18945378]

b= [0.37363935]

Epoch: 0006 cost= 0.402982056 W= [0.18423039]

b= [0.42670402]

Epoch: 0007 cost= 0.390155882 W= [0.17946766]

b= [0.47508836]

Epoch: 0008 cost= 0.378874570 W= [0.17512502]

b= [0.5192052]

Epoch: 0009 cost= 0.368932009 W= [0.17116545]

b= [0.55943096]

Optimization Finished!

Training cost= [0.368932] W= [0.17116545] b=  
[0.55943096]

W2:={0.16528997, 0.22420149, 0.21591327, 0.2083  
{0.16528997, 0.22420149, 0.21591327, 0.20835607  
b2:={-0.08805541, 0.020639995, 0.10483948, 0.181  
{-0.08805541, 0.020639995, 0.10483948, 0.181612  
dim(W2)=dim(b2)

11=11

#### 4. Iteration mit tensorflow:

=====

Startwerte per Zufall ausgewählt: W= [-0.9822901]  
b= [-0.32099992]  
Epoch: 0000 cost= 0.515979826 W= [0.22043358]  
b= [0.058935374]  
Epoch: 0010 cost= 0.356591940 W= [0.16605784]  
b= [0.6113189]  
Epoch: 0020 cost= 0.310448349 W= [0.14446126]  
b= [0.8307175]  
Epoch: 0030 cost= 0.294828981 W= [0.13588344]  
b= [0.91785926]  
Epoch: 0040 cost= 0.289052278 W= [0.13247648]  
b= [0.95247066]  
Epoch: 0050 cost= 0.286825418 W= [0.13112327]  
b= [0.9662177]  
Epoch: 0060 cost= 0.285951734 W= [0.13058577]  
b= [0.9716777]  
Epoch: 0070 cost= 0.285606116 W= [0.13037232]

```
b= [0.9738466]
Epoch: 0080 cost= 0.285469115 W= [0.13028754]
b= [0.974708]
Epoch: 0090 cost= 0.285414904 W= [0.13025387]
b= [0.9750499]
Optimization Finished!
Training cost= [0.28539455] W= [0.13024136] b=
[0.97517717]
```

```
W3:={-0.9822901, 0.22043358, 0.16605784, 0.1444
      {-0.9822901, 0.22043358, 0.16605784, 0.14446126
b3:={-0.32099992, 0.058935374, 0.6113189, 0.8307
      {-0.32099992, 0.058935374, 0.6113189, 0.8307175
dim(W3)=dim(b3)
```

12=12

STAT-Menü 

### Skript:

```
python3
```

```
'''
```

A linear regression learning algorithm example using TensorFlow library.

Author: Aymeric Damien

Project:

<https://github.com/aymericdamien/TensorFlow-Examples/>

```
'''
```

```
from __future__ import print_function
```

```

import tensorflow as tf
from numpy import *
import numpy
import matplotlib.pyplot as plt
rng = numpy.random

# Parameters
learning_rate = 0.0001
training_epochs = 1000
display_step = 50

# Training Data
train_X =
numpy.asarray([3.3, 4.4, 5.5, 6.71, 6.93, 4.168, 9.7
7.042, 10.791, 5.313, 7.997, 5.654, 9.27, 3.1])
train_Y =
numpy.asarray([1.7, 2.76, 2.09, 3.19, 1.694, 1.573,
2.827, 3.465, 1.65, 2.904, 2.42, 2.94, 1.3])

train_X=numpy.asarray(train_X)
train_Y=numpy.asarray(train_Y)
n_samples = train_X.shape[0]

# tf Graph Input
X = tf.placeholder("float")

```

```

Y = tf.placeholder("float")

# Set model weights
W = tf.Variable(rng.randn(), name="weight")
b = tf.Variable(rng.randn(), name="bias")

# Construct a linear model
pred = tf.add(tf.multiply(X, W), b)

# Mean squared error
cost = tf.reduce_sum(tf.pow(pred-Y,
2))/(2*n_samples)
# Gradient descent
optimizer =
tf.train.GradientDescentOptimizer(learning_rate).minimize

# Initializing the variables
init = tf.global_variables_initializer()

# Launch the graph
with tf.Session() as sess:
    sess.run(init)
    # Fit all training data
    for epoch in range(training_epochs):
        for (x, y) in zip(train_X, train_Y):
            sess.run(optimizer, feed_dict={X: x, Y:
y})
        # Display logs per epoch step

```

```

        if (epoch+1) % display_step == 0:
            c = sess.run(cost, feed_dict={X:
train_X, Y:train_Y})
            print("Epoch:", '%04d' % (epoch+1),
"cost=", "{:.9f}".format(c), \
                "W=", sess.run(W), "b=",
sess.run(b))
            print("Optimization Finished!")
            training_cost = sess.run(cost, feed_dict={X:
train_X, Y: train_Y})
            print("Training cost=", training_cost, "W=",
sess.run(W), "b=", sess.run(b), '\n')
            # Graphic display
            plt.plot(train_X, train_Y, 'ro', label='Original
data')
            plt.plot(train_X, sess.run(W) * train_X +
sess.run(b), label='Fitted line')
            plt.legend()
            plt.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.
>>> '''

```

```

... A linear regression learning algorithm example using
TensorFlow library.
... Author
... Project:
https://github.com/aymericdamien/TensorFlow-Examples/
... """
'\nA linear regression learning algorithm example using
TensorFlow library. \nAuthor\nProject:
https://github.com/aymericdamien/TensorFlow-Example▶
>>>
>>> from __future__ import print_function
>>>
>>> import tensorflow as tf
>>> from numpy import *
>>> import numpy
>>> import matplotlib.pyplot as plt
>>> rng = numpy.random
>>>
>>> # Parameters
... learning_rate = 0.0001
>>> training_epochs = 1000
>>> display_step = 50
>>>
>>> # Training Data
... train_X =
numpy.asarray([3.3, 4.4, 5.5, 6.71, 6.93, 4.168, 9.7▶
...
7.042, 10.791, 5.313, 7.997, 5.654, 9.27, 3.11])
>>> train_Y =

```



```

numpy.asarray([1.7, 2.76, 2.09, 3.19, 1.694, 1.573,
...
2.827, 3.465, 1.65, 2.904, 2.42, 2.94, 1.3])
>>>
>>> train_X=numpy.asarray(train_X)
>>> train_Y=numpy.asarray(train_Y)
>>> n_samples = train_X.shape[0]
>>>
>>>
>>> # tf Graph Input
... X = tf.placeholder("float")
>>> Y = tf.placeholder("float")
>>>
>>> # Set model weights
... W = tf.Variable(rng.randn(), name="weight")
>>> b = tf.Variable(rng.randn(), name="bias")
>>>
>>> # Construct a linear model
... pred = tf.add(tf.multiply(X, W), b)
>>>
>>>
>>> # Mean squared error
... cost = tf.reduce_sum(tf.pow(pred-Y,
2))/(2*n_samples)
>>> # Gradient descent
... optimizer =
tf.train.GradientDescentOptimizer(learning_rate).minimi
>>>
>>> # Initializing the variables

```

```

... init = tf.global_variables_initializer()
>>>
>>> # Launch the graph
... with tf.Session() as sess:
...     sess.run(init)
...     # Fit all training data
...     for epoch in range(training_epochs):
...         for (x, y) in zip(train_X, train_Y):
...             sess.run(optimizer, feed_dict={X:
x, Y: y})
...         # Display logs per epoch step
...         if (epoch+1) % display_step == 0:
...             c = sess.run(cost, feed_dict={X:
train_X, Y:train_Y})
...             print("Epoch:", "%04d" %
(epoch+1), "cost=", "{:.9f}".format(c), \
...                 "W=", sess.run(W), "b=",
sess.run(b))
...         print("Optimization Finished!")
...         training_cost = sess.run(cost, feed_dict={X:
train_X, Y: train_Y})
...         print("Training cost=", training_cost, "W=",
sess.run(W), "b=", sess.run(b), '\n')
...         # Graphic display
...         plt.plot(train_X, train_Y, 'ro', label='Original
data')
...         plt.plot(train_X, sess.run(W) * train_X +
sess.run(b), label='Fitted line')
...         plt.legend()

```

```
...     plt.show()
...
Epoch: 0050 cost= 20.454841614 W= -0.5383804 b=
-0.39039218
Epoch: 0100 cost= 13.073741913 W= -0.34863567
b= -0.3629717
Epoch: 0150 cost= 8.375241280 W= -0.19726828 b=
-0.34096542
Epoch: 0200 cost= 5.384352684 W= -0.07651979 b=
-0.32327884
Epoch: 0250 cost= 3.480441332 W= 0.019800002 b=
-0.30903846
Epoch: 0300 cost= 2.268455029 W= 0.096629456 b=
-0.29754832
Epoch: 0350 cost= 1.496913791 W= 0.15790887 b=
-0.2882516
Epoch: 0400 cost= 1.005744100 W= 0.2067818 b=
-0.280706
Epoch: 0450 cost= 0.693045378 W= 0.24575654 b=
-0.27455688
Epoch: 0500 cost= 0.493956745 W= 0.2768339 b=
-0.2695219
Epoch: 0550 cost= 0.367188901 W= 0.3016104 b=
-0.26537654
Epoch: 0600 cost= 0.286457956 W= 0.32135987 b=
-0.26194048
Epoch: 0650 cost= 0.235033110 W= 0.33709866 b=
-0.2590707
Epoch: 0700 cost= 0.202264324 W= 0.34963745 b=
```

-0.2566525  
Epoch: 0750 cost= 0.181371331 W= 0.3596235 b=  
-0.2545948  
Epoch: 0800 cost= 0.168038592 W= 0.36757308 b=  
-0.25282508  
Epoch: 0850 cost= 0.159519732 W= 0.37389737 b=  
-0.25128493  
Epoch: 0900 cost= 0.154065475 W= 0.37892509 b=  
-0.2499282  
Epoch: 0950 cost= 0.150562286 W= 0.38291833 b=  
-0.24871752  
Epoch: 1000 cost= 0.148301467 W= 0.38608623 b=  
-0.24762374  
Optimization Finished!  
Training cost= 0.14830147 W= 0.38608623 b=  
-0.24762374

[<matplotlib.lines.Line2D object at 0x7f791c0e89e8>]  
[<matplotlib.lines.Line2D object at 0x7f7921150860>]  
<matplotlib.legend.Legend object at 0x7f791c0fd198>

=====

**Anlage:**

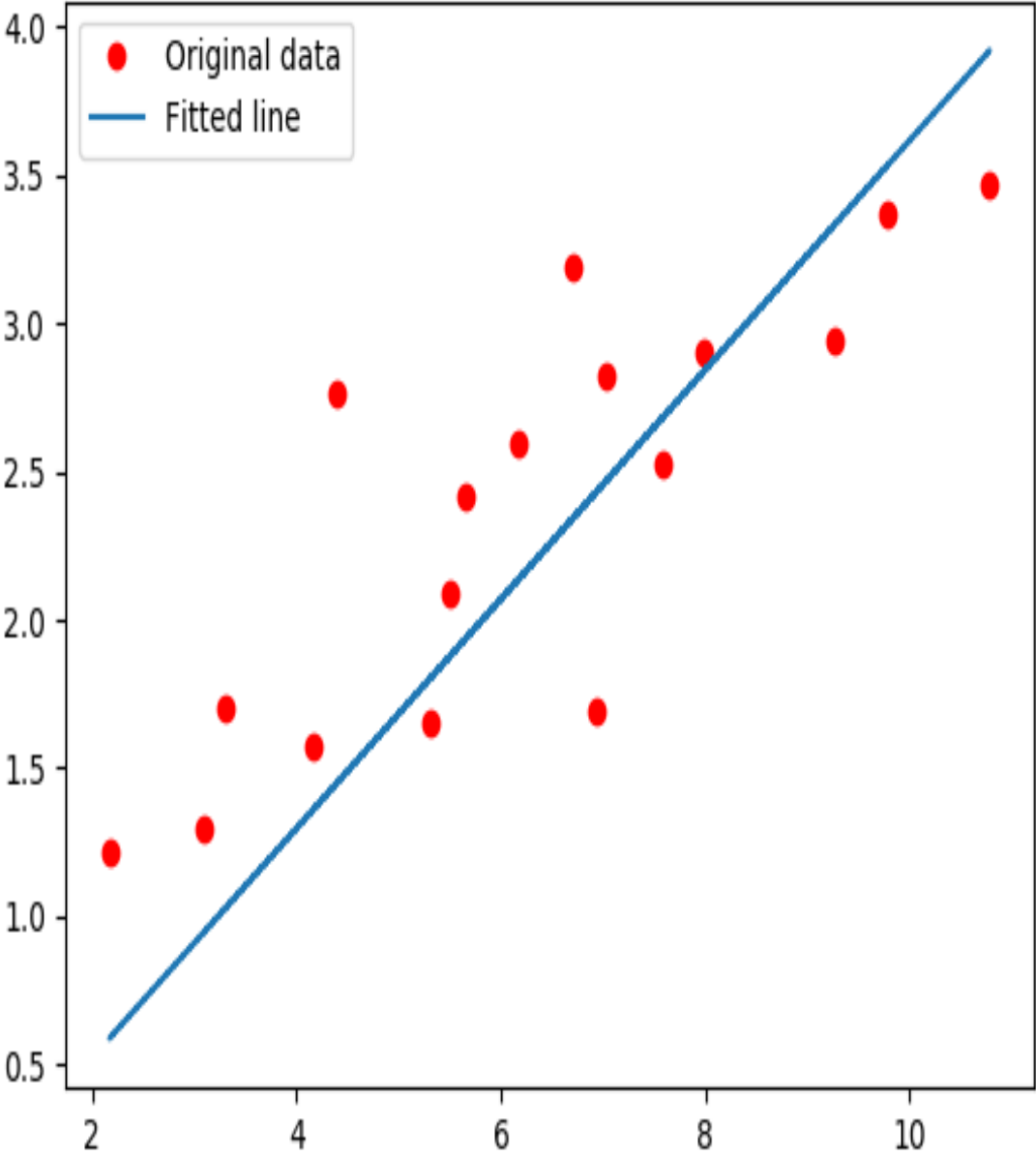
**Bilder mit Zielfunktion bei linearer Regression**

**Download für dieses Dokument:**

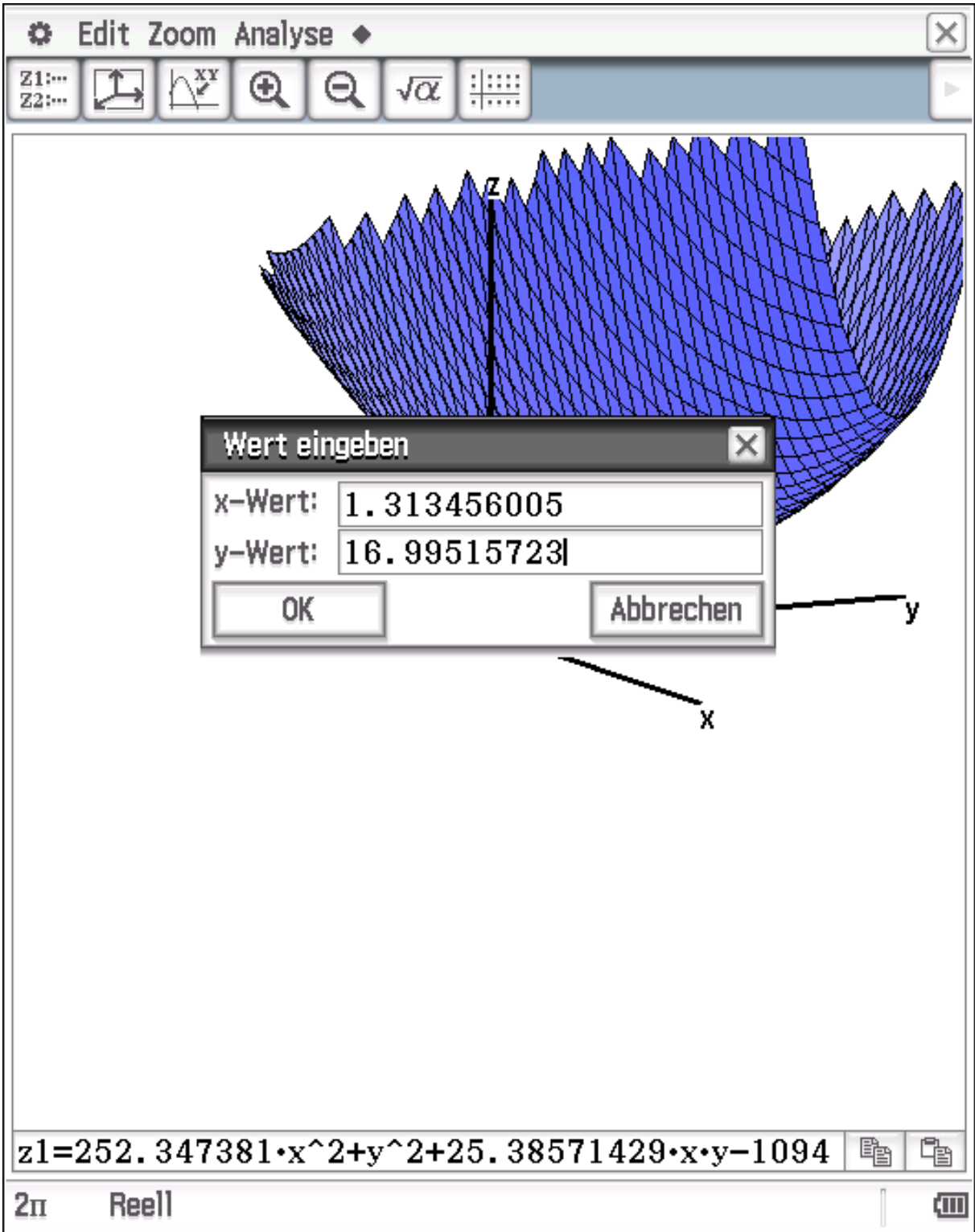
[www.informatik.htw-dresden.de/](http://www.informatik.htw-dresden.de/)

[~paditz/Tensorflow-Ue09.pdf](#)

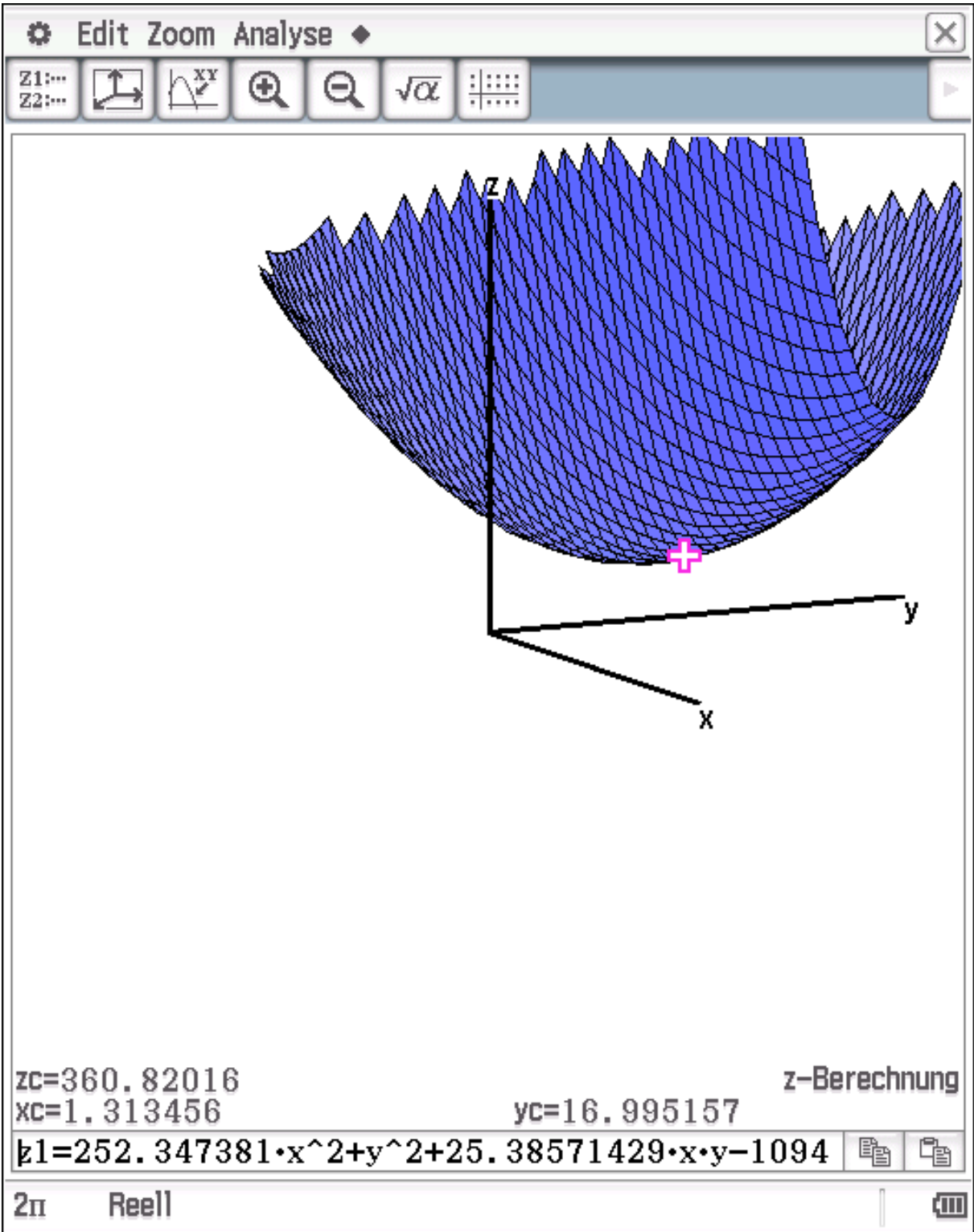
**Lineare Regression: (n=17, Trainingsdaten)**



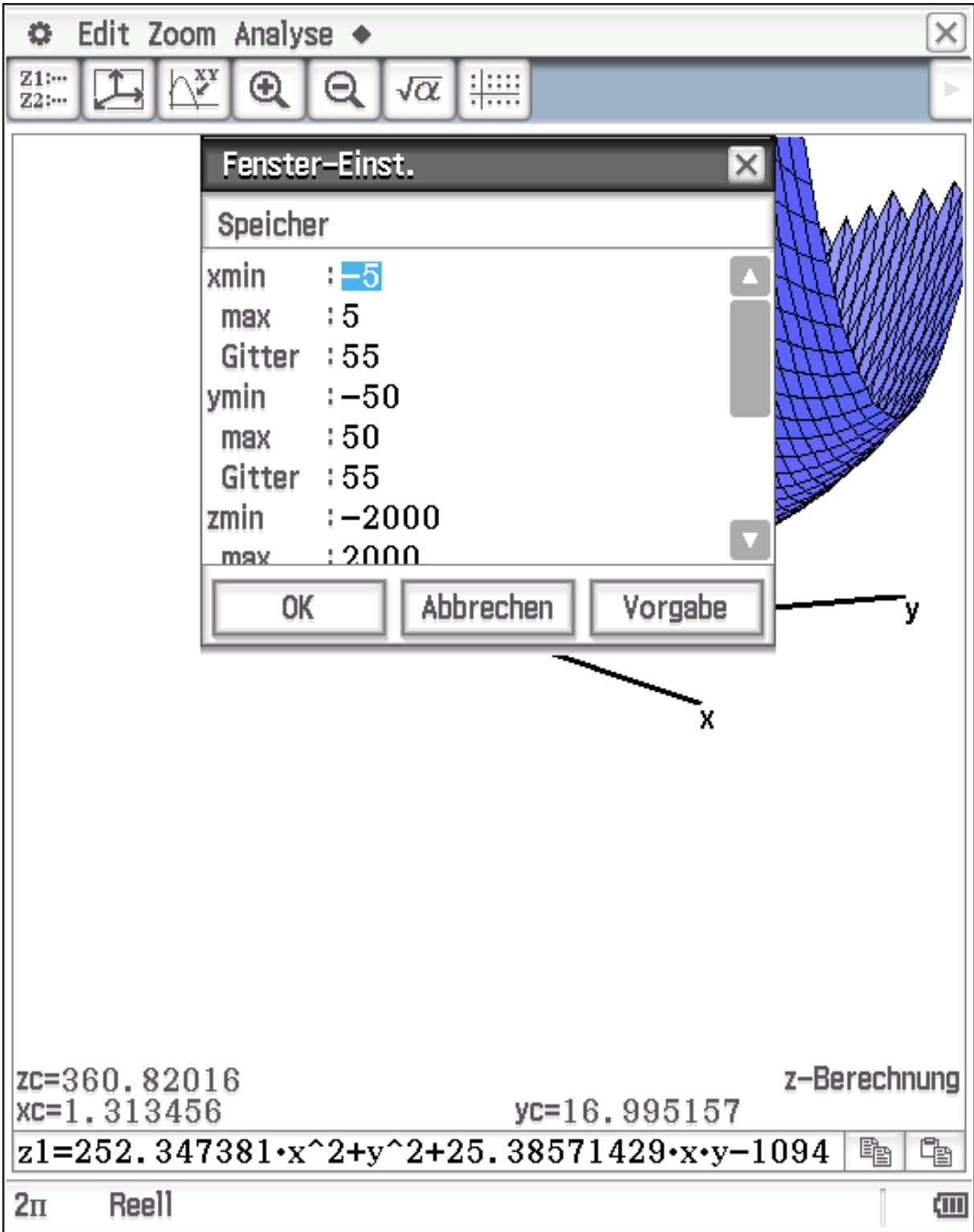
### 3D-Grafik der Verlustfunktion loss(W,b)



Das globale Min. von  $\text{loss}(W,b)$  ist erreicht:

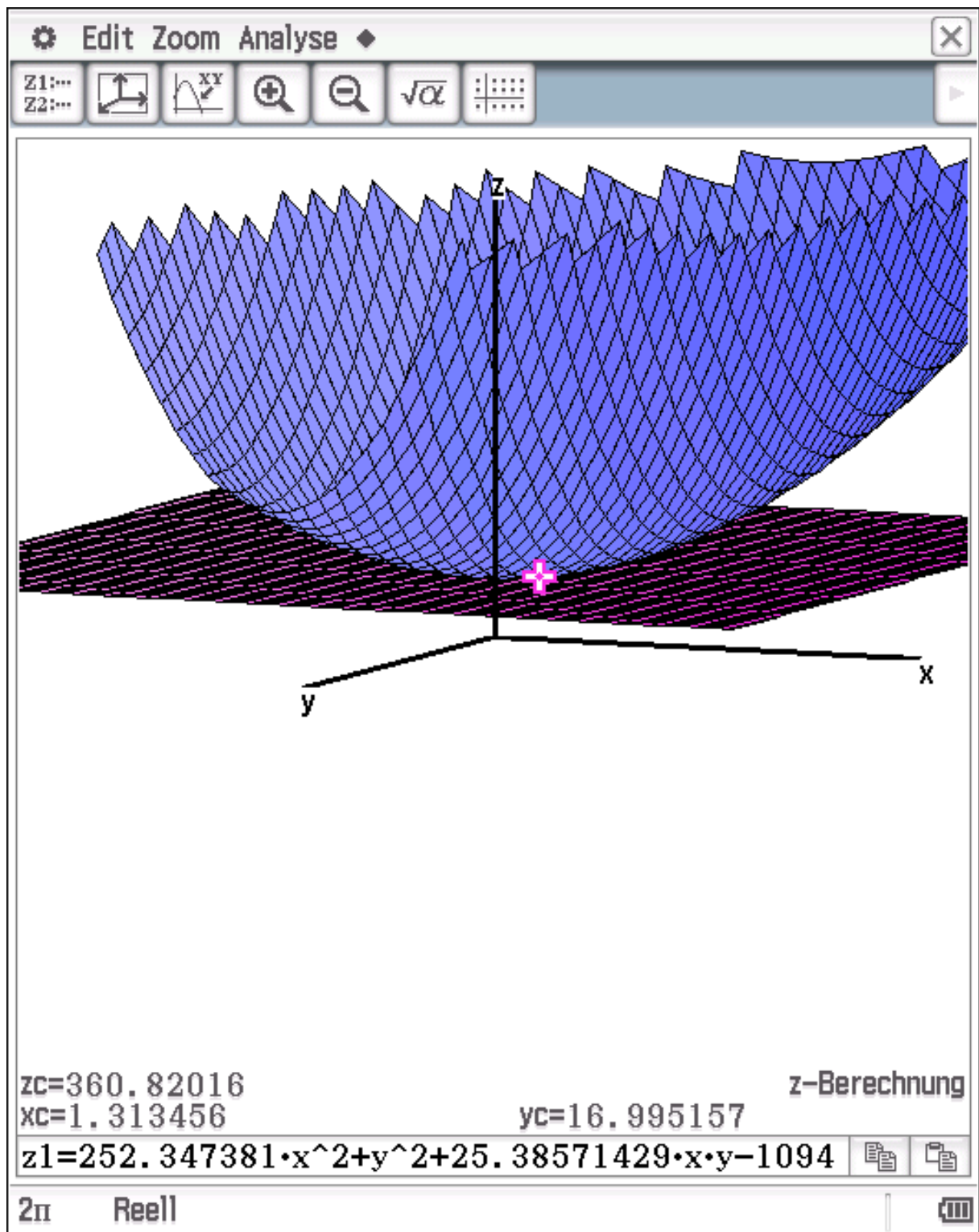


Betrachtungsfenstereinstellung:

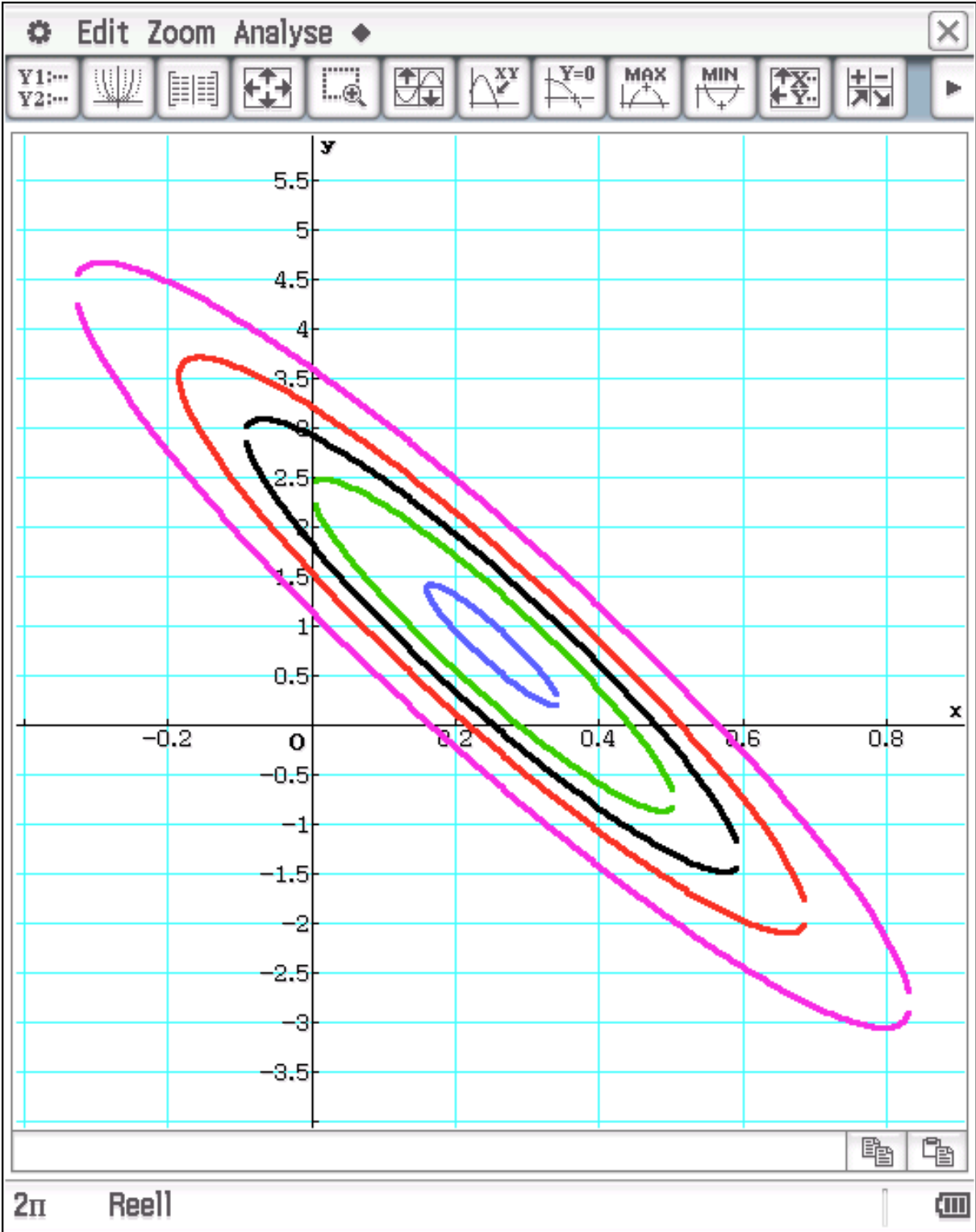




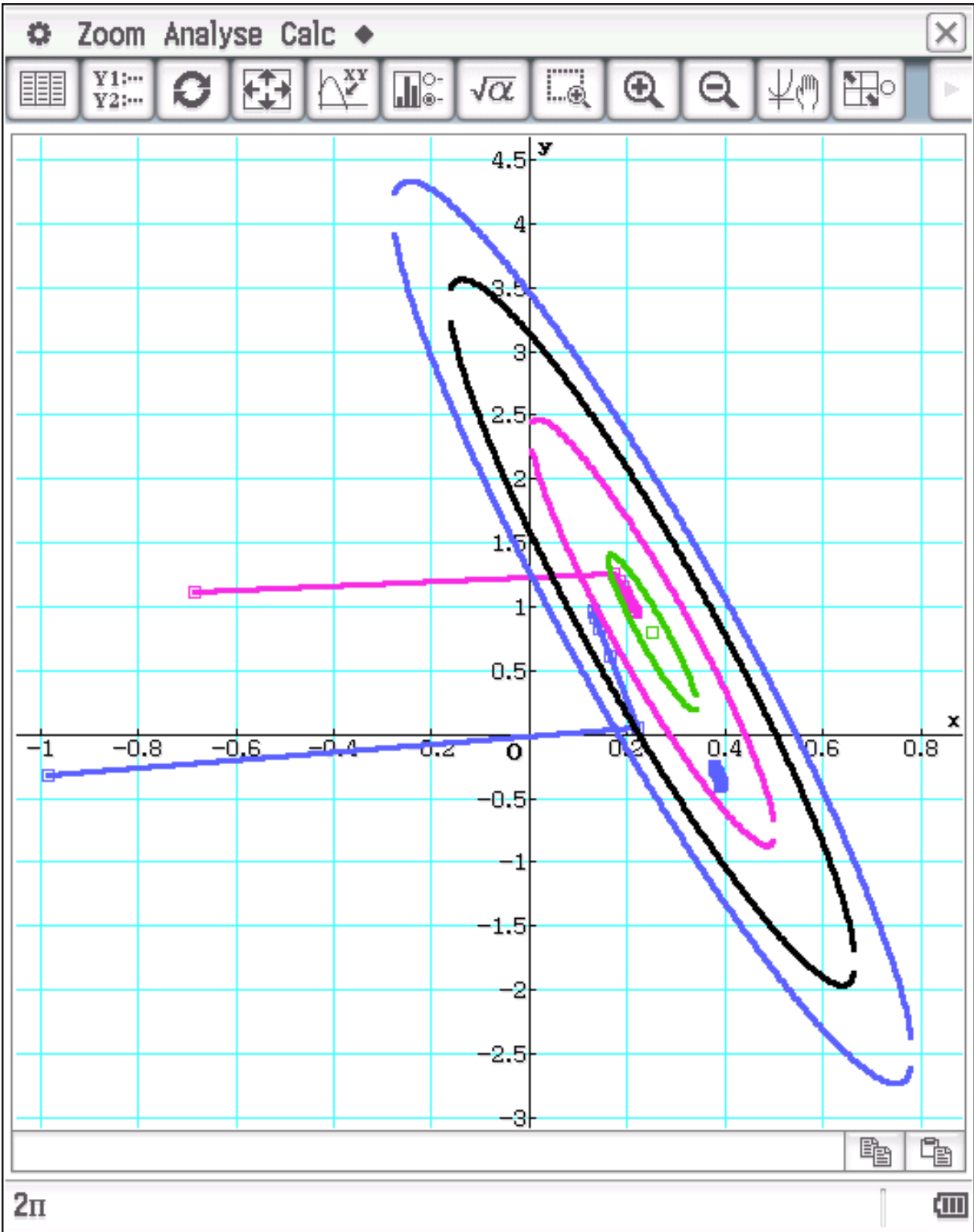
## Minimum mit waagerechter Tangentialebene:



**Höhenlinien der loss-Funktion:**



# Iteration mit Tensorflow:



Bei zu großer Schrittweite kann das Verfahren divergieren:

