Cost estimation for precast columns

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Outline

Source Data

Source Excel file

		Stützentyp		Stützenform			Abmessungen				Last				Eingekauft durch		Preis									Ratios			
Datum	Bezeichnung	Stahlbetonstütze	Stahlbetonverbundstütze	rund	eckig	oval	urchmess	a	b	l	Nd	Md	Stück	Hersteller	intern	extern	intern	Rabatt inkl. Skonto	Transport	intern inkl. Rabatt & Teuerung & Transport	extern	Rabatt inkl. Skonto	extern inkl. Rabatt & Teuerung	A	V	N/mm²	CHF/m³	Teuerung	Preis Total inkl. Rabatt & Teuerung & Transport
							[m	[m	[m	[m	[kN	[kNm]					[CHF	[%	[CH	[CHF]	[CHF]	[%	[CHF]	[m²	[m³				[CHF
12.01.2011		x		x			0.350			4.77	7'100		3	Firma 2	x		2'561	18.0%		2'730				0.0962	0.459	73.8	5'949	30.0%	8'190
12.01.2011		x		x			0.300			4.77	4'800		10	Firma 2	x		2'065	18.0%		2'201				0.0707	0.337	67.9	6'529	30.0%	22'013
12.01.2011		x		x			0.300			2.85	6'000		2	Firma 2	x		1'698	18.0%		1'810				0.0707	0.201	84.9	8'985	30.0%	3'620
12.01.2011		x		x			0.300			2.83	5'000		3	Firma 2	x		1'484	18.0%		1'582				0.0707	0.200	70.7	7'908	30.0%	4'746
12.01.2011		x		x			0.300			2.80	7'100		15	Firma 2	x		2'058	18.0%		2'194				0.0707	0.198	100.4	11'084	30.0%	32'907
12.01.2011		x		x			0.350			2.80	8'600		3	Firma 2	x		2'319	18.0%		2'472				0.0962	0.269	89.4	9'176	30.0%	7'416
12.01.2011		x		x			0.300			2.73	7'000		6	Firma 2	x		1'988	18.0%		2'119				0.0707	0.193	99.0	10'982	30.0%	12'715
12.01.2011		x		x			0.350			2.73	8'300		5	Firma 2	x		2'090	18.0%		2'228				0.0962	0.263	86.3	8'482	30.0%	11'140
12.01.2011		x		x			0.300			2.68	2'500		1	Firma 2	x		914	18.0%		974				0.0707	0.189	35.4	5'143	30.0%	974
12.01.2011		x		x			0.300			2.63	4'000		10	Firma 2	x		1'170	18.0%		1'247				0.0707	0.186	56.6	6'709	30.0%	12'472
12.01.2011		x		x			0.350			3.28	6'600		1	Firma 2	x		1'714	18.0%		1'827				0.0962	0.316	68.6	5'790	30.0%	1'827
12.01.2011		x		x			0.300			2.98	4'000		2	Firma 2	x		1'134	18.0%		1'209				0.0707	0.211	56.6	5'739	30.0%	2'418
12.01.2011		x		x			0.300			2.95	6'600		14	Firma 2	x		1'709	18.0%		1'822				0.0707	0.209	93.4	8'737	30.0%	25'505
12.01.2011		x		x			0.300			2.95	7'500		7	Firma 2	x		1'872	18.0%		1'996				0.0707	0.209	106.1	9'570	30.0%	13'969
12.01.2011		x		x			0.300			2.90	3'200		5	Firma 2	x		814	18.0%		868				0.0707	0.205	45.3	4'233	30.0%	4'339
12.01.2011		x		x			0.300			2.88	6'600		3	Firma 2	x		1'540	18.0%		1'642				0.0707	0.204	93.4	8'064	30.0%	4'925
12.01.2011		x		x			0.300			2.81	4'000		2	Firma 2	x		1'087	18.0%		1'159				0.0707	0.199	56.6	5'834	30.0%	2'317
12.01.2011		x		x			0.300			2.75	4'000		3	Firma 2	x		970	18.0%		1'034				0.0707	0.194	56.6	5'319	30.0%	3'102
12.01.2011		x		x			0.300			2.70	2'000		2	Firma 2	x		692	18.0%		738				0.0707	0.191	28.3	3'865	30.0%	1'475
12.01.2011		x		x			0.300			2.66	4'000		3	Firma 2	x		951	18.0%		1'014				0.0707	0.188	56.6	5'392	30.0%	3'041
12.01.2011		x		x			0.300			2.28	3'500		3	Firma 2	x		786	18.0%		838				0.0707	0.161	49.5	5'199	30.0%	2'514
12.01.2011		x			x			0.30	0.30	2.28	3'000		1	Firma 2	x		656	18.0%		699				0.0900	0.205	33.3	3'408	30.0%	699
12.01.2011		x		x			0.300			3.80	6'600		26	Firma 2	x		2'076	18.0%		2'213				0.0707	0.269	93.4	8'239	30.0%	57'538
12.01.2011		x		x			0.300			3.80	4'000		24	Firma 2	x		1'247	18.0%		1'329				0.0707	0.269	56.6	4'949	30.0%	31'903
12.01.2011			x	x			0.159			2.62	700		18	Firma 2	x		744	12.0%		851				0.0199	0.052	35.3	16'361	30.0%	15'320
12.11.2011			x	x			0.133			2.62	450		19	Firma 2	x		601	12.0%		688				0.0139	0.036	32.4	18'889	30.0%	13'063
27.08.2012		x			x			0.40	0.40	3.60	4'200		18	Firma 6	x		688	24.0%		680				0.1600	0.576	26.3	1'180	30.0%	12'235
27.08.2012		x			x			0.30	0.30	3.60	700		12	Firma 6	x		527	24.0%		521				0.0900	0.324	7.8	1'607	30.0%	6'248
27.08.2012		x			x			0.30	0.30	3.27	2'900		33	Firma 6	x		550	24.0%		543				0.0900	0.294	32.2	1'846	30.0%	17'932
27.08.2012		x			x			0.25	0.25	3.23	1'200		34	Firma 6	x		394	24.0%		391				0.0625	0.201	19.2	1'944	30.0%	13'302

Source Data

DataFrame.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3447 entries, 0 to 3446
Data columns (total 33 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   Ort                                   0 non-null      float64
 1   Projektname                           0 non-null      float64
 2   Datum                                 3447 non-null   datetime64[ns]
 3   Bezeichnung                           0 non-null      float64
 4   Stahlbetonstütze                      3312 non-null   object
 5   Stahlbetonverbundstütze               135 non-null    object
 6   rund                                  724 non-null    object
 7   eckig                                 2373 non-null   object
 8   oval                                  253 non-null    object
 9   d                                     724 non-null    float64
 10  a                                     2626 non-null   float64
 11  b                                     2626 non-null   float64
 12  l                                     3447 non-null   float64
 13  Nd                                    3447 non-null   int64
 14  Md                                    98 non-null     float64
 15  Stück                                 3447 non-null   int64
 16  Hersteller                            3447 non-null   object
 17  Einkauf_LoMa                          3447 non-null   object
 18  Einkauf_Baumeister                    0 non-null      float64
 19  LoMa                                  3447 non-null   float64
 20  Rabatt inkl. Skonto LoMa              3382 non-null   float64
 21  Transport                             2212 non-null   float64
 22  Stückpreis                            3447 non-null   float64
 23  Baumeister                            0 non-null      float64
 24  Rabatt inkl. Skonto Baumeister        0 non-null      float64
 25  Baumeister inkl. Rabatt & Teuerung    0 non-null      float64
 26  A                                     3447 non-null   float64
 27  V                                     3447 non-null   float64
 28  N/mm2                                 3447 non-null   float64
 29  CHF/m3                                3447 non-null   float64
 30  Teuerung                              3447 non-null   float64
 31  Total Preis                           3447 non-null   float64
 32  Bemerkungen                           1493 non-null   object
dtypes: datetime64[ns](1), float64(22), int64(2), object(8)
memory usage: 888.8+ KB
```

Source Data

some words on metadata

A Colum types

A.1 steel/concrete composite columns

Figur 6: Typische Verbundquerschnitte und Bezeichnungen

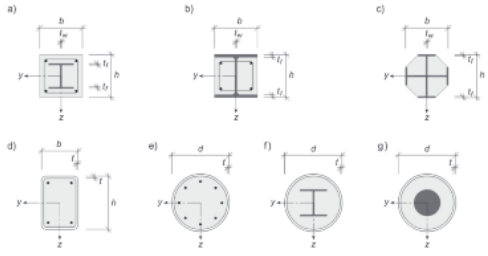


FIGURE A.1: SIA 264 [8] Figure 6, steel/concrete composite columns

A.2 reinforced concrete columns

Figur 14: Druckglieder mit Umschnürungsbewehrung

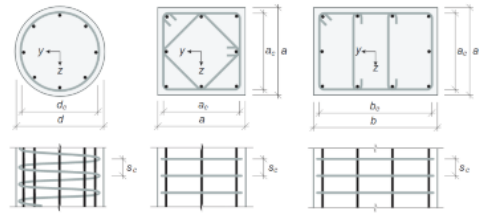


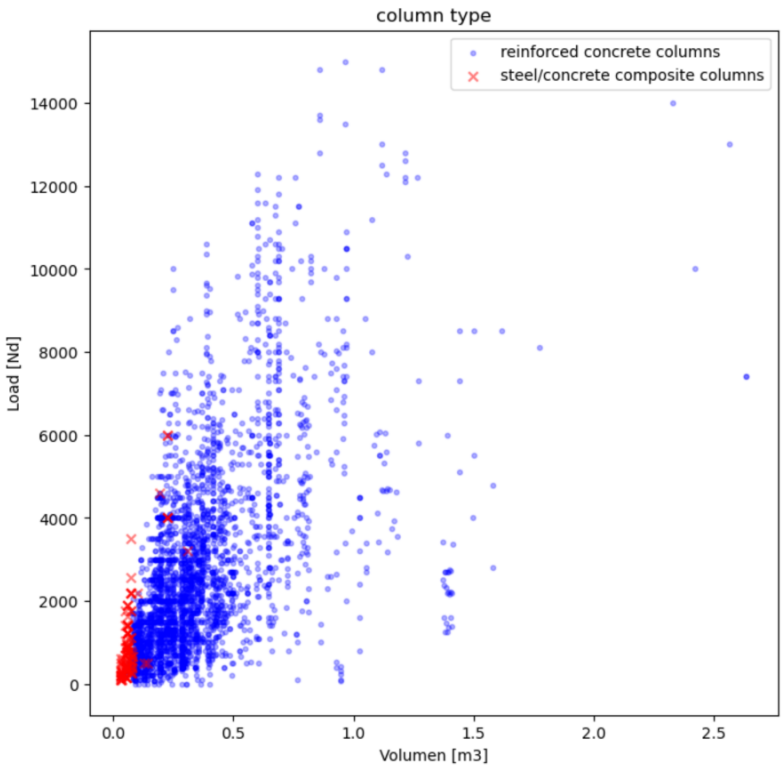
FIGURE A.2: SIA 262 [9] Figure 14, reinforced concrete columns

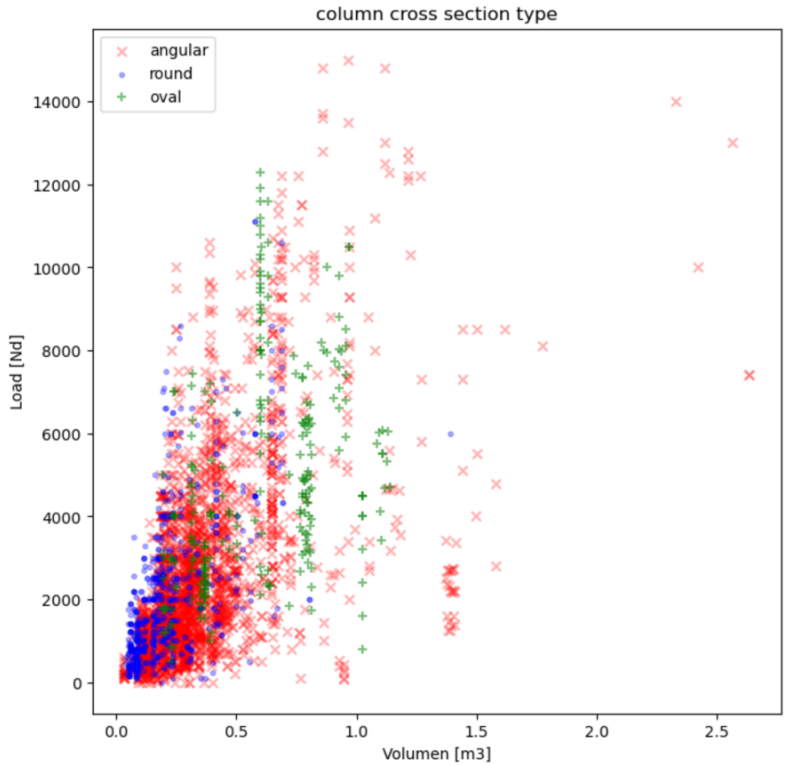
Data cleaning

Considered data range:

load:	$0 < N_d < 15'000$
bending moment:	$M_d < 50$
diameter:	$0.10 < d < 0.50$
width:	$0.10 < a < 1.0$
length:	$0.10 < b < 1.0$
column length:	$2.0 < l < 15.0$

Scatter plots





Procedure

top down (with linear model and neural network)

1. all data
2. column type
3. column type and cross-section
4. cross-section

The prediction accuracy should not fall below 70%

TABLE 7.2: Considered columns/feature

column/feature	**variable name**
load	Nd
cross-section area	A
column length	l
volume	V
unit price	Stückpreis

TABLE 7.3: Normalization of columns/feature

column/feature	**adjustment**
load	Nd/10000
cross-section area	A x 10
column length	l/10
volume	V
unit price	Stückpreis/10000

Neural Network

- input shape 4
- 3 Layers with activation function *relu*
- last layer without activation function, as I'm looking for numbers
- neurons per layer (128, 64, 64, 32, 1)
- loss function *mse*
- metrics function r^2
- epoch 256

all data - linear model

```
MSE:
Train: 324
Test: 363

R2:
Train: 0.7097
Test: 0.6972
```

```
MSE:
Train: 340
Test: 296

R2:
Train: 0.7097
Test: 0.6928
```

```
MSE:
Train: 325
Test: 356

R2:
Train: 0.7287
Test: 0.6028
```

```
MSE:
Train: 329
Test: 343

R2:
Train: 0.7041
Test: 0.7202
```

all data - linear model

```
MSE:
Train: 329
Test: 343

R2:
Train: 0.7041
Test: 0.7202

Intercept: -70.2744
Coeficent Nd: 0.1313
Coeficent A: -5440.8351
Coeficent V: 1548.3899
Coeficent l: 175.4642
```

OLS Regression Results

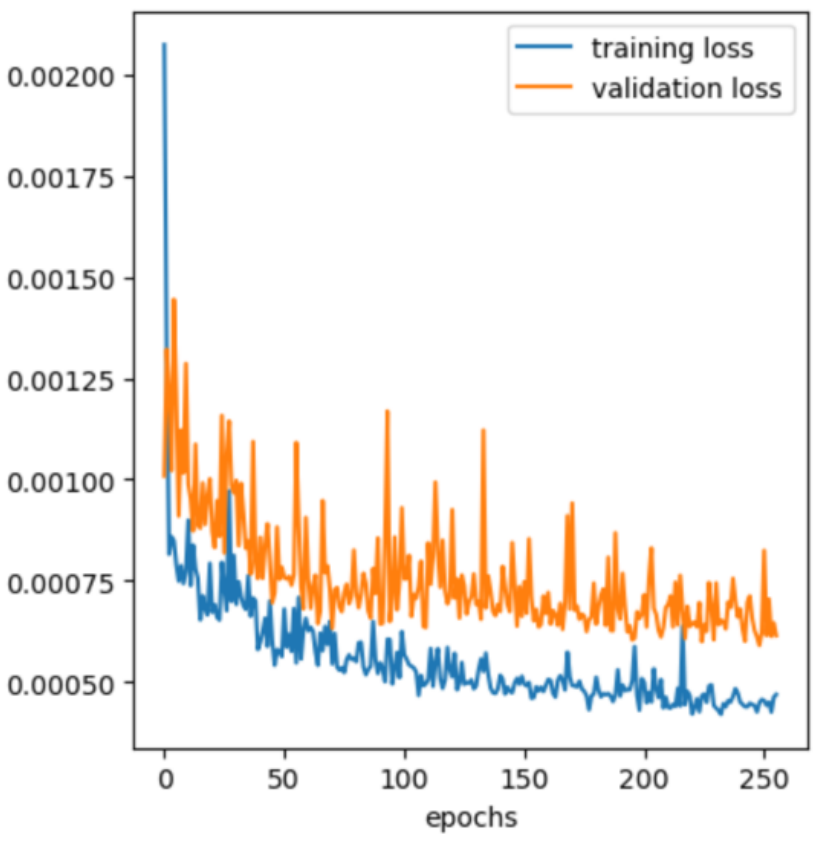
Dep. Variable:	Stückpreis	R-squared:	0.704
Model:	OLS	Adj. R-squared:	0.704
Method:	Least Squares	F-statistic:	1605.
Date:	Sun, 20 Nov 2022	Prob (F-statistic):	0.00
Time:	15:02:10	Log-Likelihood:	-19499.
No. Observations:	2703	AIC:	3.901e+04
Df Residuals:	2698	BIC:	3.904e+04
Df Model:	4		
Covariance Type:	nonrobust		

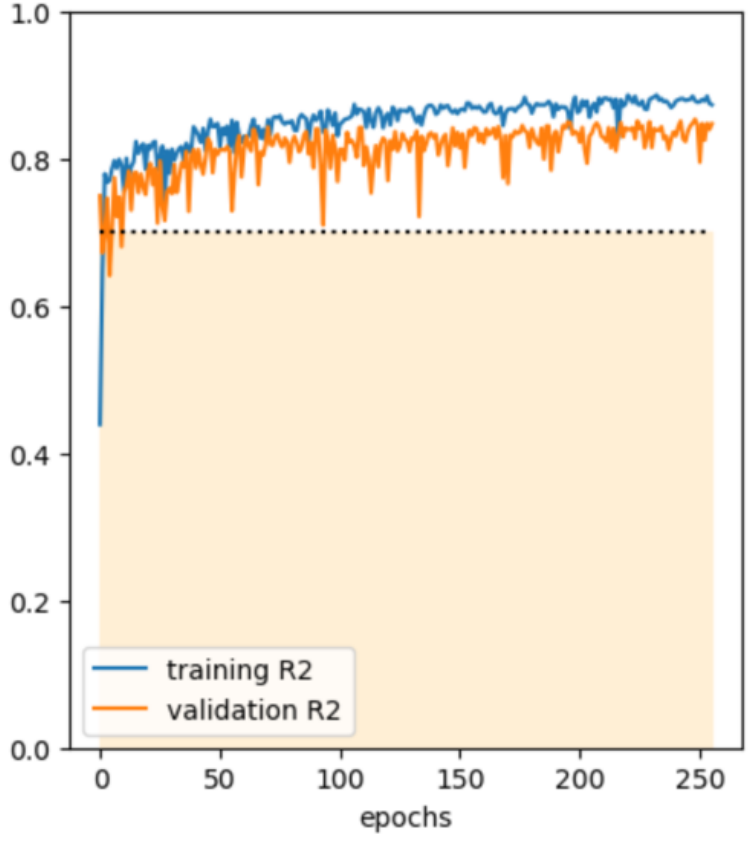
	coef	std err	t	P>|t|	[0.025	0.975]
const	-70.2744	51.818	-1.356	0.175	-171.881	31.333
Nd	0.1313	0.004	36.027	0.000	0.124	0.138
A	-5440.8351	397.038	-13.704	0.000	-6219.364	-4662.306
V	1548.3899	112.573	13.754	0.000	1327.651	1769.129
l	175.4642	15.991	10.973	0.000	144.109	206.819

Omnibus:	1120.405	Durbin-Watson:	1.952
Prob(Omnibus):	0.000	Jarque-Bera (JB):	12892.447
Skew:	1.638	Prob(JB):	0.00
Kurtosis:	13.185	Cond. No.	2.39e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.39e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

all data - neural network






```
22/22 - 0s - loss: 6.1461e-04 - r_square: 0.8474 - 37ms/epoch - 2ms/step
```

```
1 xin = np.array([[2500/10000, .25*.25*10, .25*.25*3, 3/10]])
2 print(f"{NN.predict(NNmodel, xin)[0][0]*10000:0.0f}")
```

```
1/1 [==============================] - 0s 19ms/step
726
```

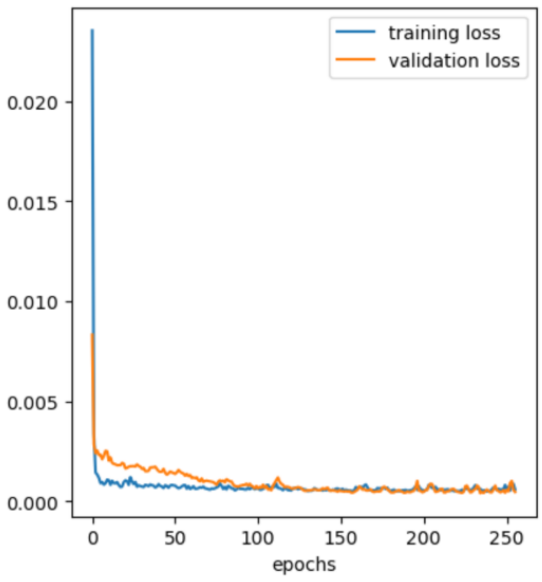
compound colums - linear model

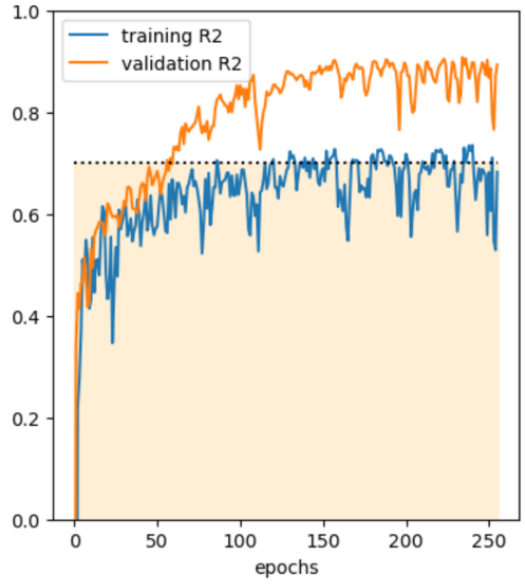
```
MSE:
Train: 190
Test: 416

R2:
Train: 0.5475
Test: 0.7510
```

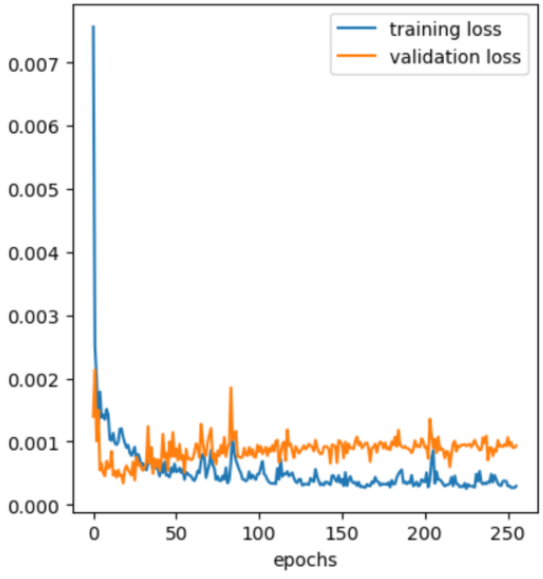
```
MSE:
Train: 244
Test: 236

R2:
Train: 0.7517
Test: 0.7120
```

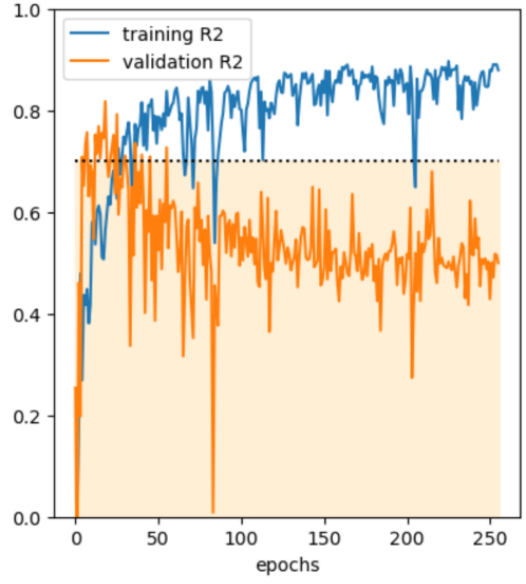
```
MSE:
Train: 245
Test: 211

R2:
Train: 0.7701
Test: 0.5621
```

compound colums - neural network









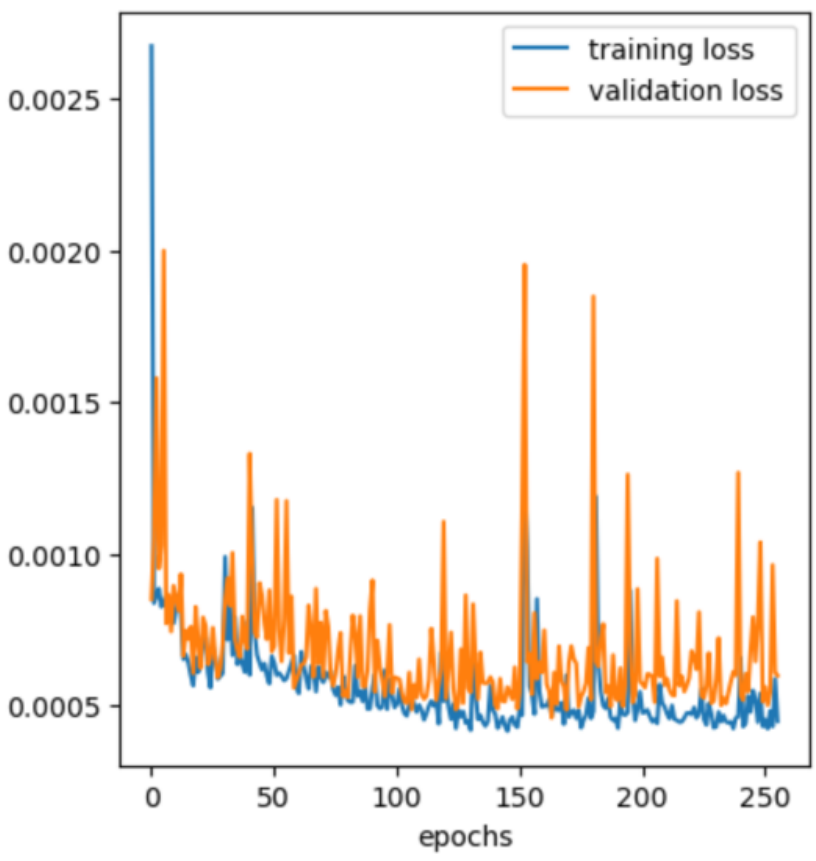
concret columns - linear model

```
MSE:
Train: 325
Test: 319

R2:
Train: 0.7282
Test: 0.7102
```

```
MSE:
Train: 328
Test: 308

R2:
Train: 0.7214
Test: 0.7405
```

```
MSE:
Train: 323
Test: 327

R2:
Train: 0.7217
Test: 0.7367
```

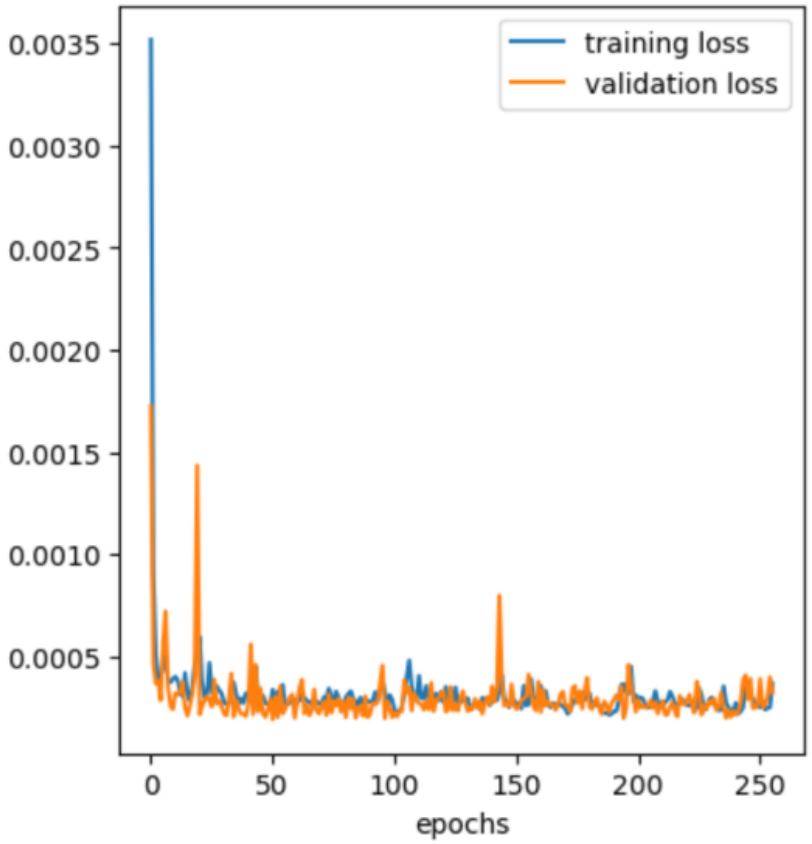
concret columns - neural network

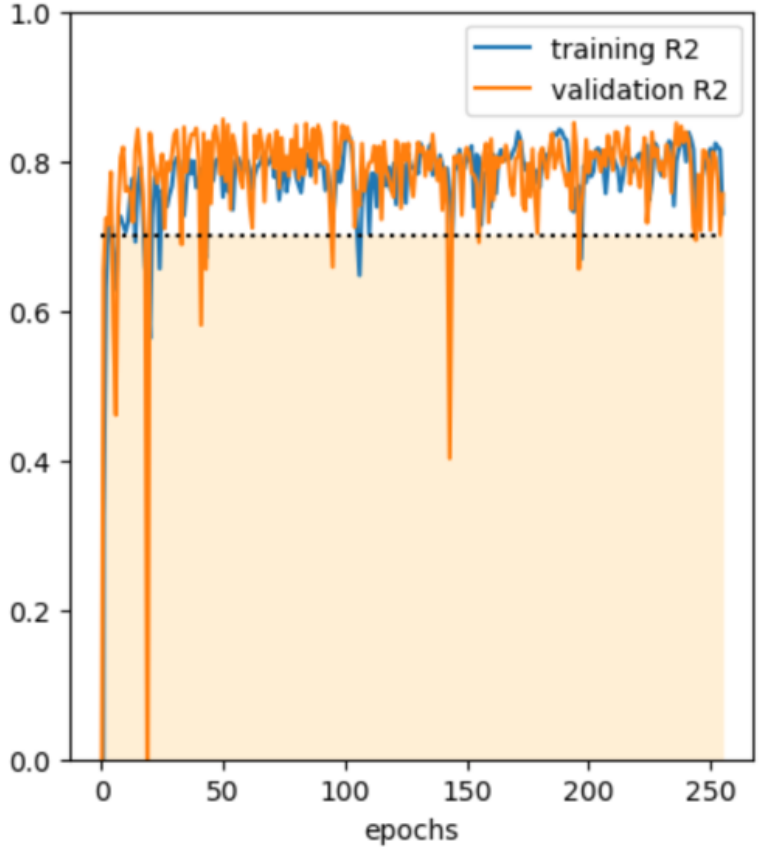



```
21/21 - 0s - loss: 5.9896e-04 - r_square: 0.8563 - 33ms/epoch - 2ms/step
```

concret columns - round

```
MSE:
198
169

R2:
0.7244
0.7432
```

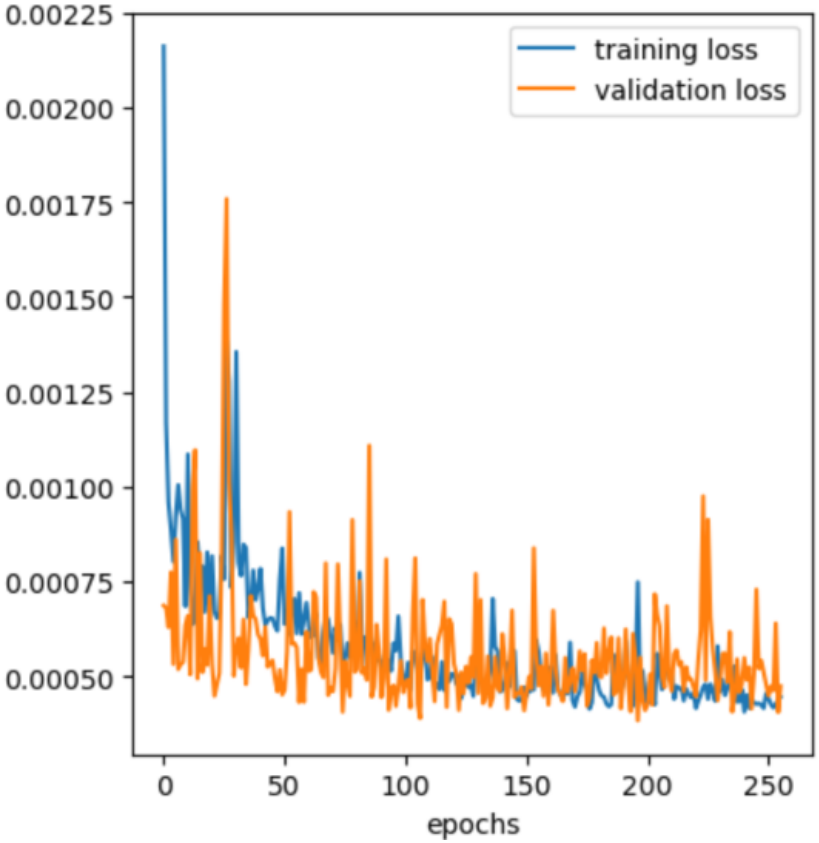


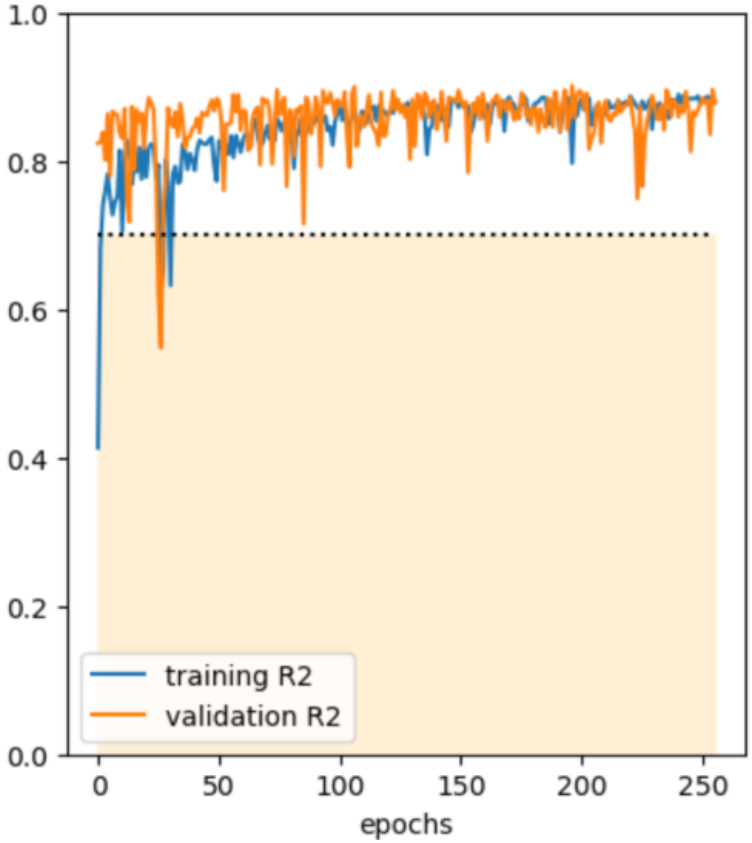


concret columns - angular

MSE:
327
331

R2:
0.7017
0.7454

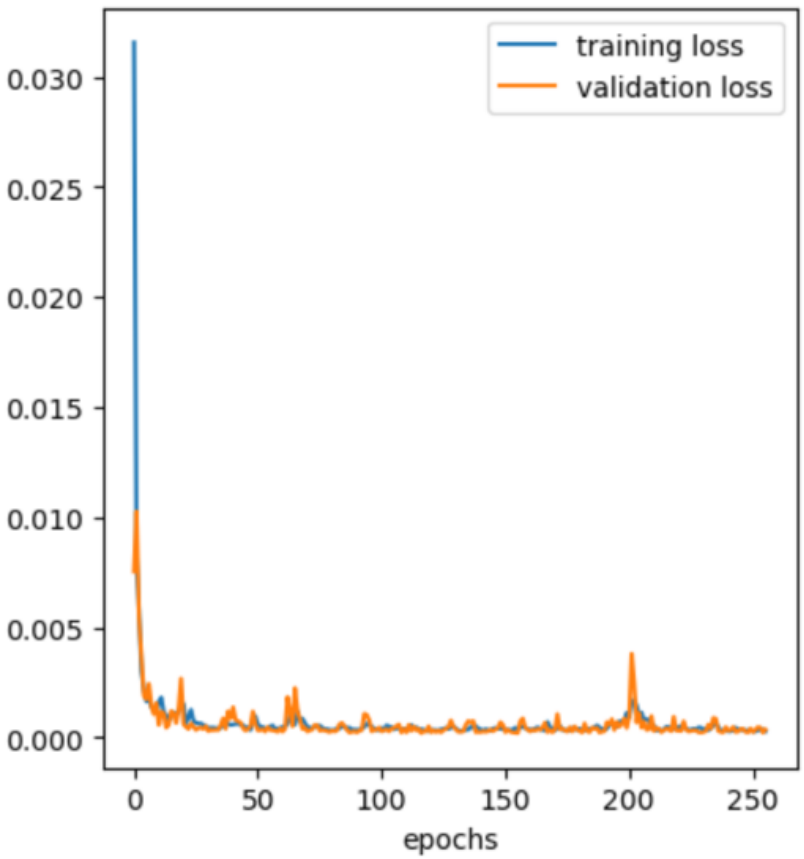


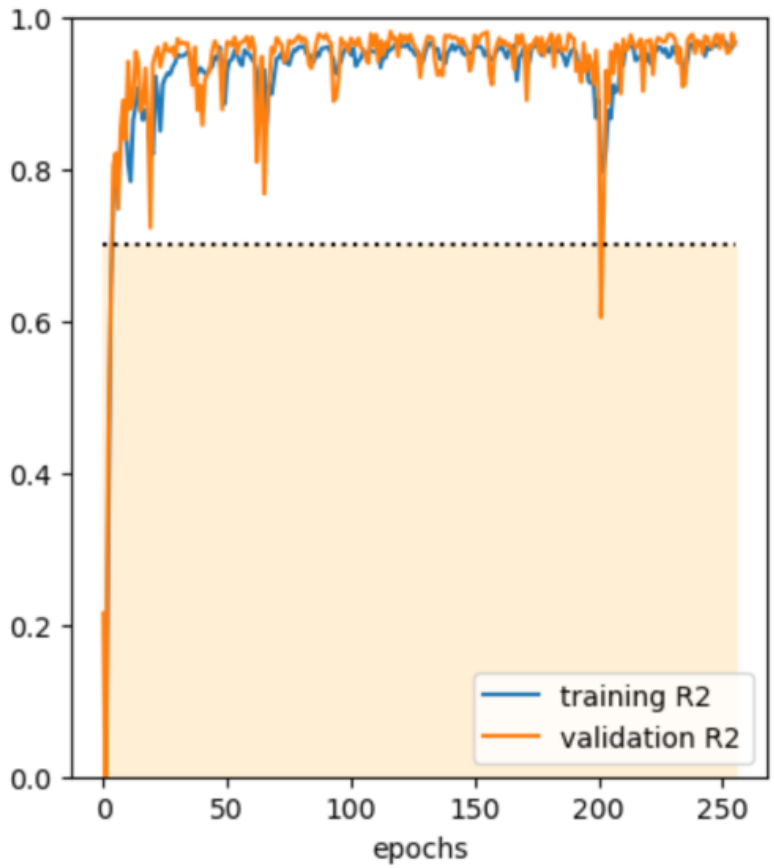


concret columns - oval

MSE:
424
432

R2:
0.7893
0.7949

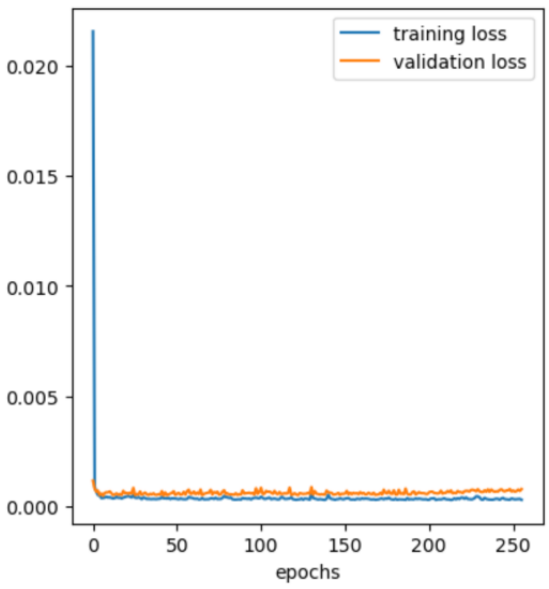


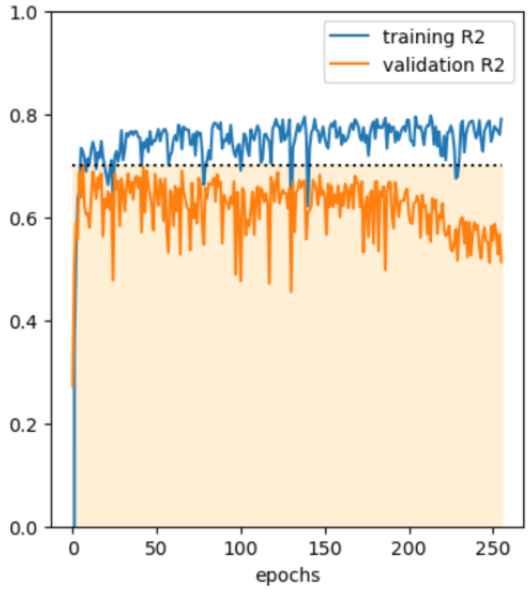


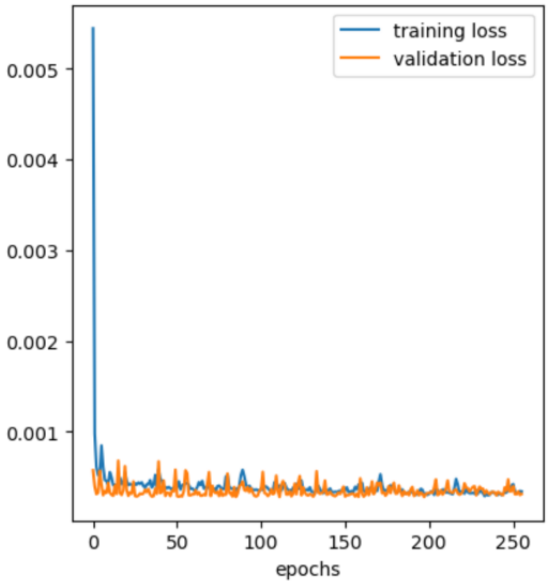
round - linear model

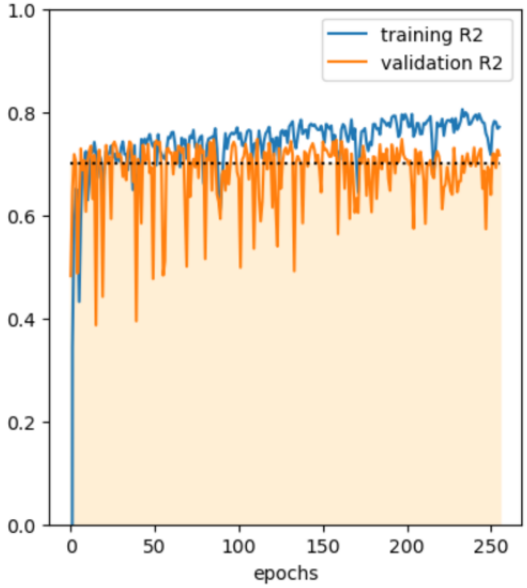
MSE:	MSE:	MSE:
224	216	217
191	224	217
R2:	R2:	R2:
0.6642	0.6803	0.6518
0.6680	0.6041	0.7156

round - neural network









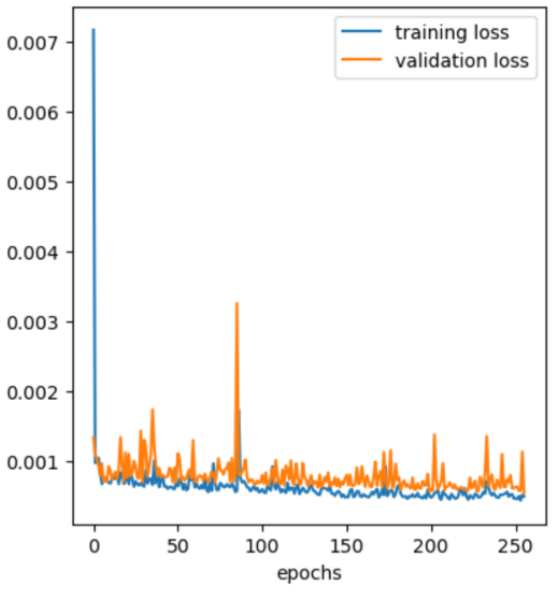
angular - linear model

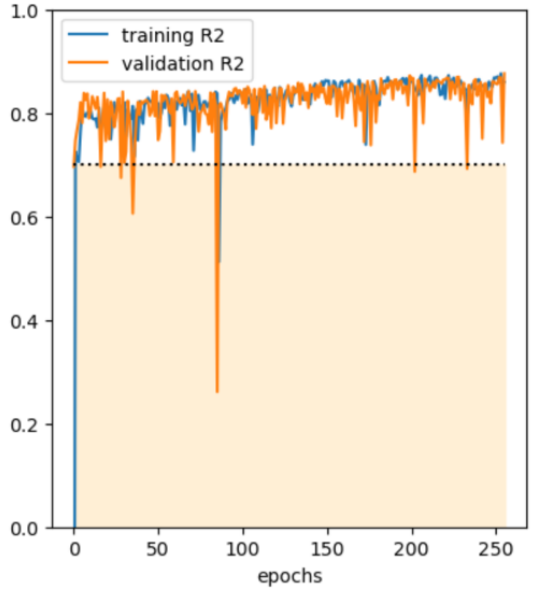
```
MSE:
332
347

R2:
0.6998
0.6972
```

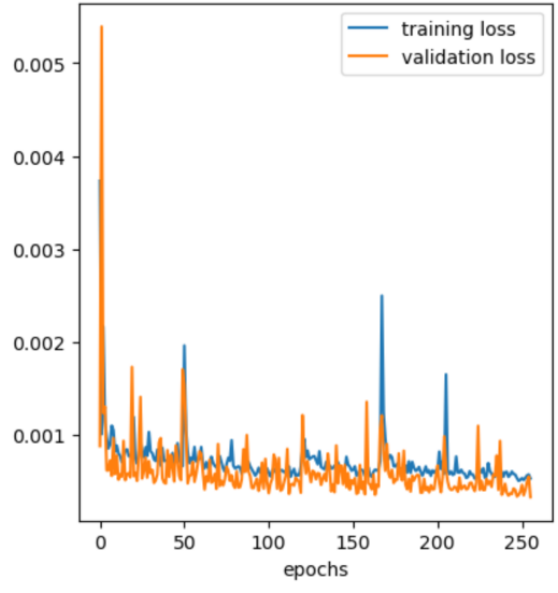
```
MSE:
316
403

R2:
0.7080
0.6718
```

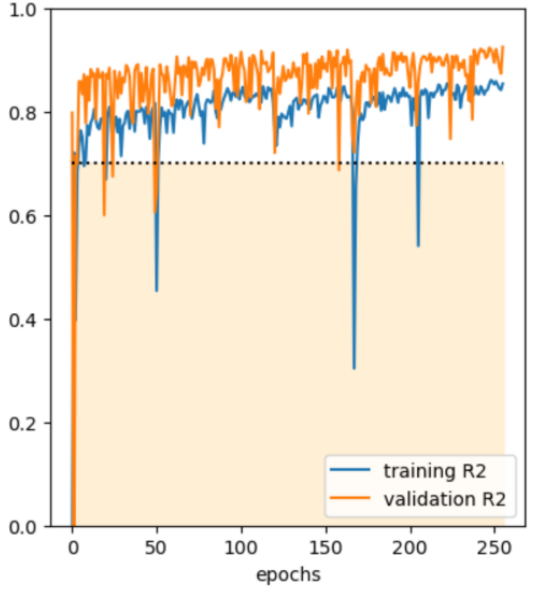
```
MSE:
342
304

R2:
0.6966
0.7119
```

angular - neural network









What if...

TABLE 7.2: Considered columns/feature

column/feature	**variable name**
load	Nd
cross-section area	A
column length	l
volume	V
unit price	Stückpreis

What if I used more/different features?

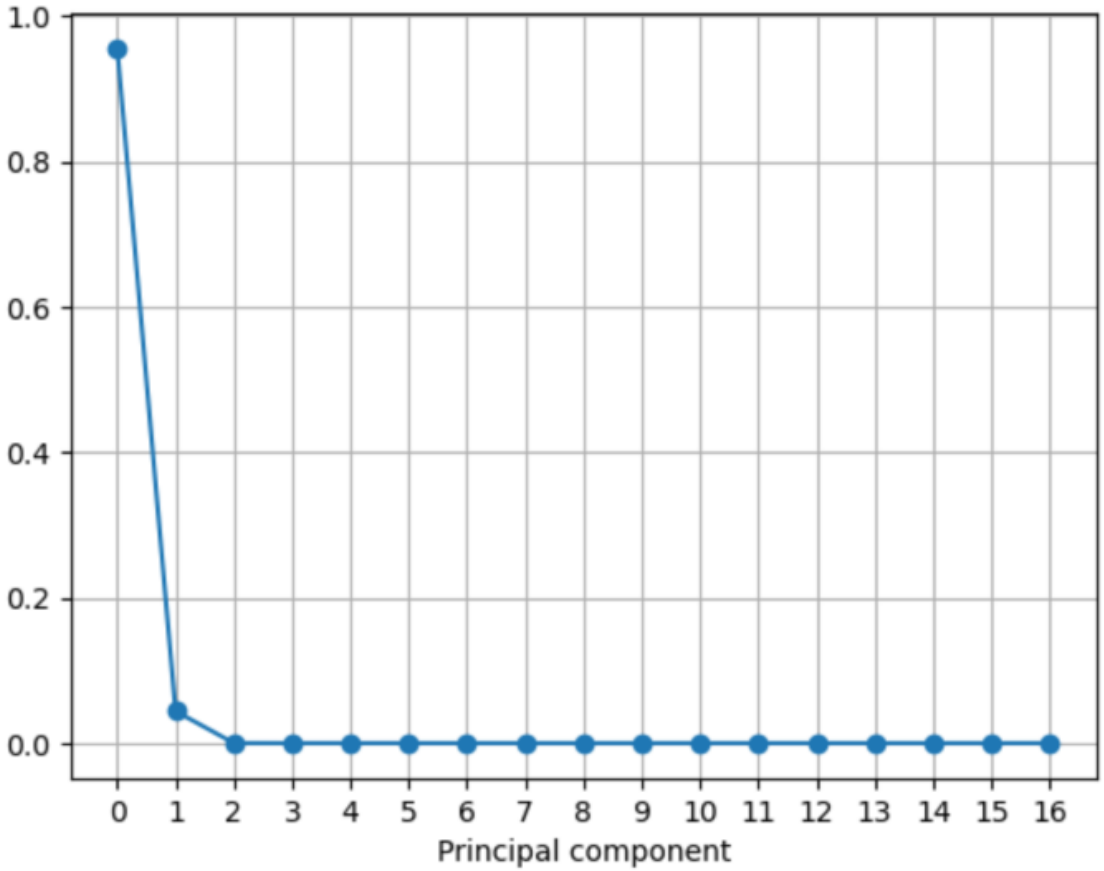
Principal Component Analysis

Reformatting the DataFrame:

- Dropping some features
- fill Nan values with 0
- replace x, X values with 1

```
df_pca = df.drop(["Datum", "Stückpreis", "Ort", "Projektname", "Bezeichnung", "Einkauf_Baumeister",
                  "Baumeister", "Rabatt inkl. Skonto Baumeister", "Baumeister inkl. Rabatt & Teuerung",
                  "Bemerkungen", "Einkauf_LoMa", "Rabatt inkl. Skonto LoMa", "Teuerung", "Hersteller", "CHF/m3",
                  "Total Preis",], axis=1)

df_pca = df_pca.fillna(0, inplace=False)

df_pca = df_pca.replace(to_replace=["x", "X"], value=[1, 1])
```

Principal Component Analysis

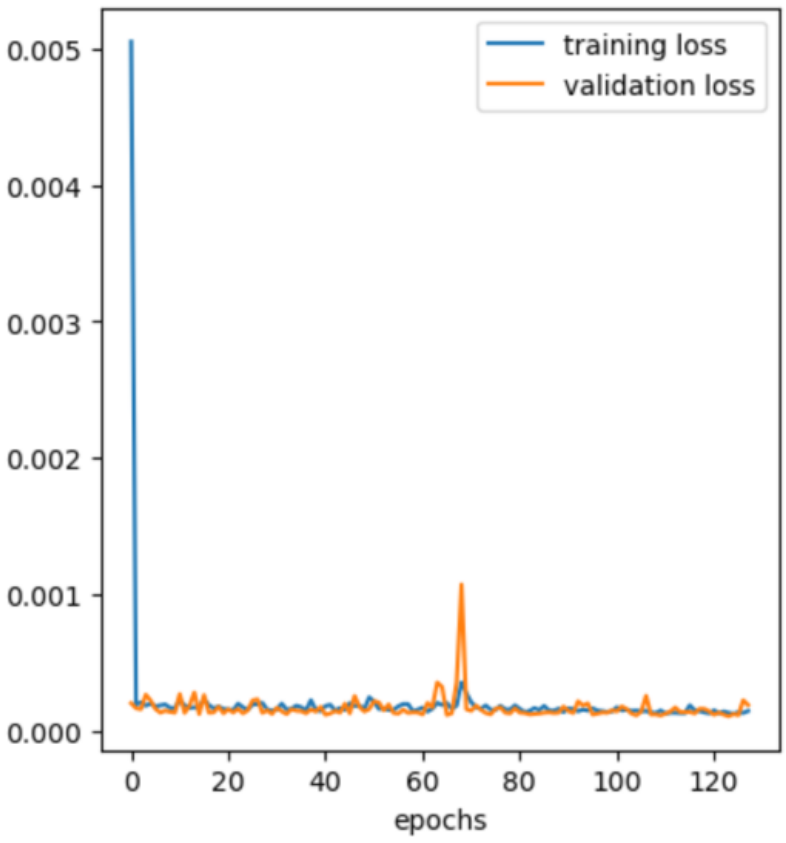


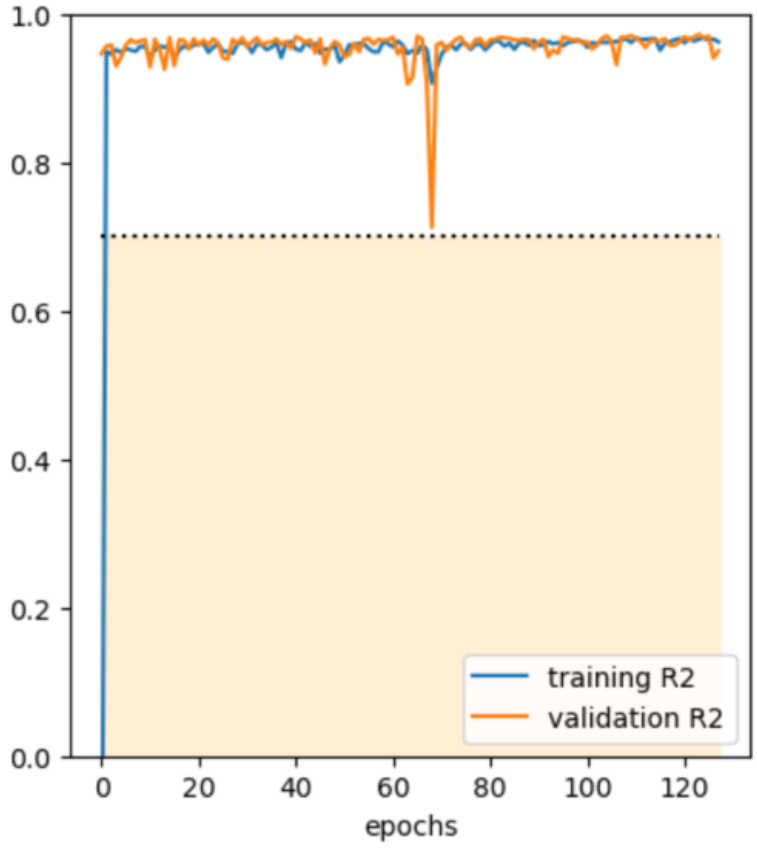
PCA - linear model & neural network

```
1 print(f"{np.sum(pca.explained_variance_ratio_[:3]):0.6f}")
```

```
0.999944
```

```
MSE:
130
118

R2:
0.9555
0.9623
```






```
22/22 - 0s - loss: 1.8603e-04 - r_square: 0.9500 - 42ms/epoch - 2ms/step
```

PCA - prediction

```
Stahlbetonstütze = 1
Stahlbetonverbundstütze = 0
rund = 0
eckig = 1
oval = 0
d = 0
a = 0.25
b = 0.25
l = 3.0
Nd = 2000
Md = 0
Stück = 1
LoMa = 1
Transport = 10
A = a * b
V = A * l
N_mm2 = Nd*1000/(A*100*100*100)
```

```
1/1 [==============================] - 0s 24ms/step
194
```

PCA - prediction

```
Stahlbetonstütze = 1
Stahlbetonverbundstütze = 0
rund = 0
eckig = 1
oval = 0
d = 0
a = 0.25
b = 0.25
l = 3.0
Nd = 2000
Md = 0
Stück = 1
LoMa = 1
Transport = 10
A = a * b
V = A * l
N_mm2 = Nd*1000/(A*100*100*100)
```

```
1/1 [==============================] - 0s 24ms/step
194
```

this is not a realistic value!

PCA - prediction

```
Stahlbetonstütze = 1
Stahlbetonverbundstütze = 0
rund = 0
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N_mm2 = Nd*1000/(A*100*100*100)
```
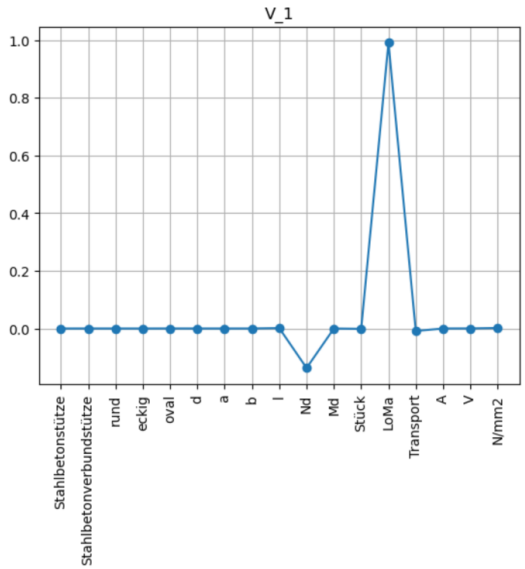

```
1/1 [==============================] - 0s 24ms/step
194
```

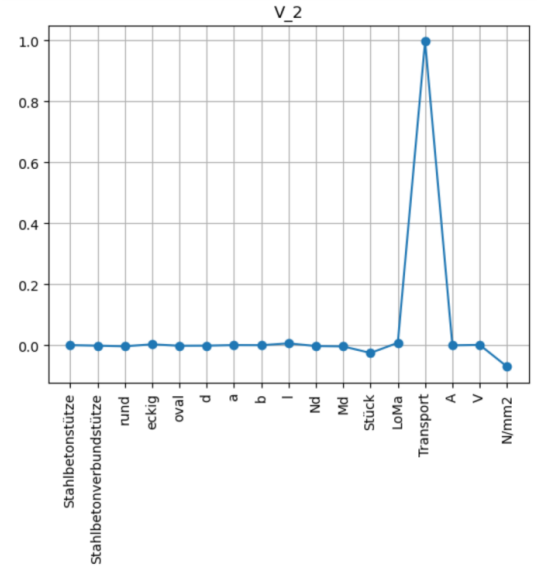
this is not a realistic value!

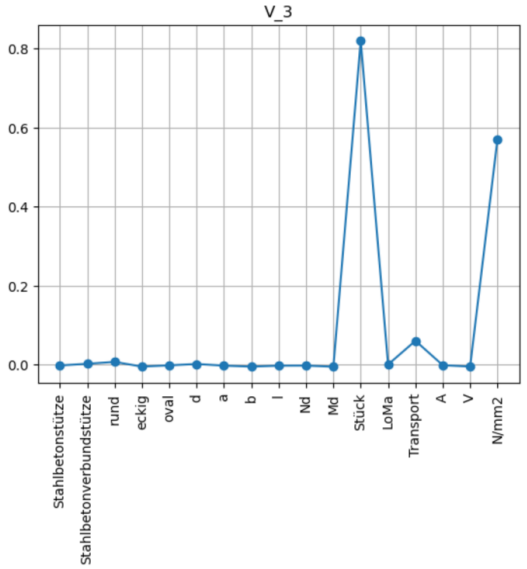
What happend?

Principal Component Analysis

first 3 components:







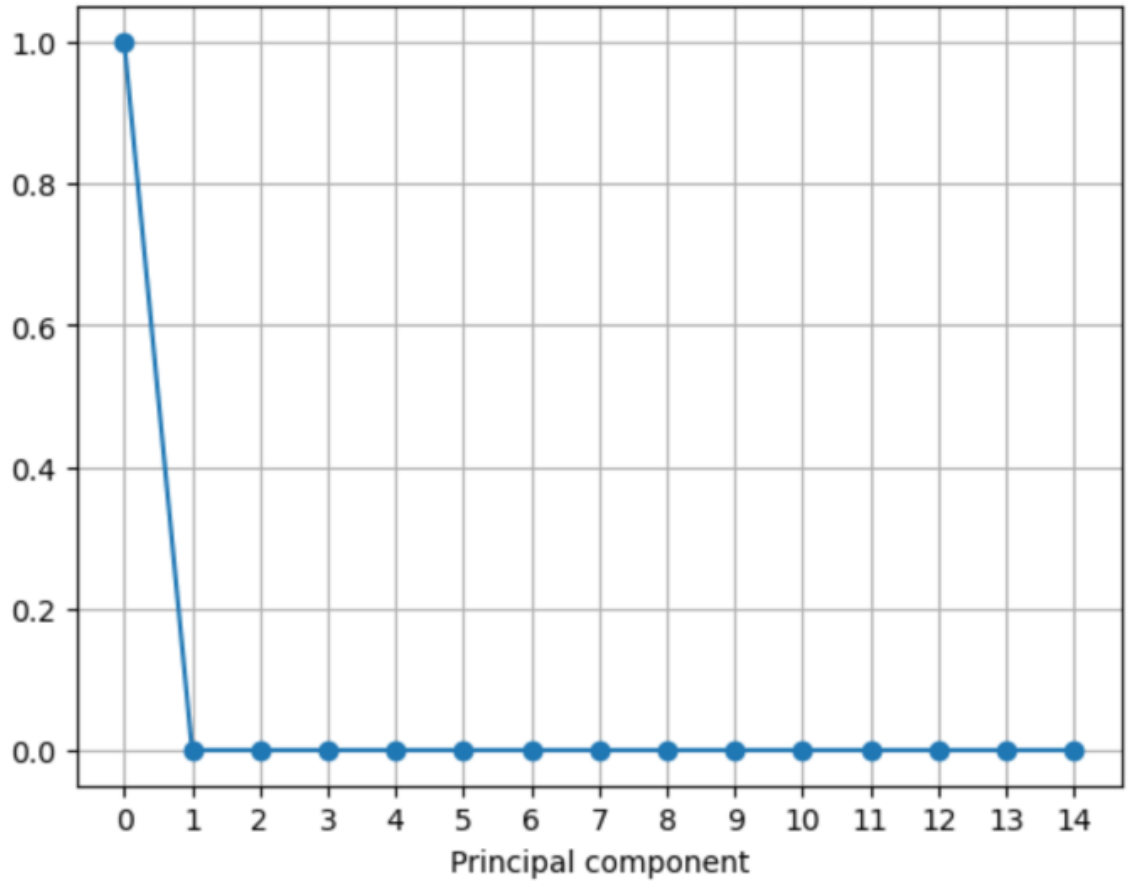
PCA round 2

Reformatting the DataFrame:

- Dropping some features
- fill Nan values with 0
- replace x, X values with 1

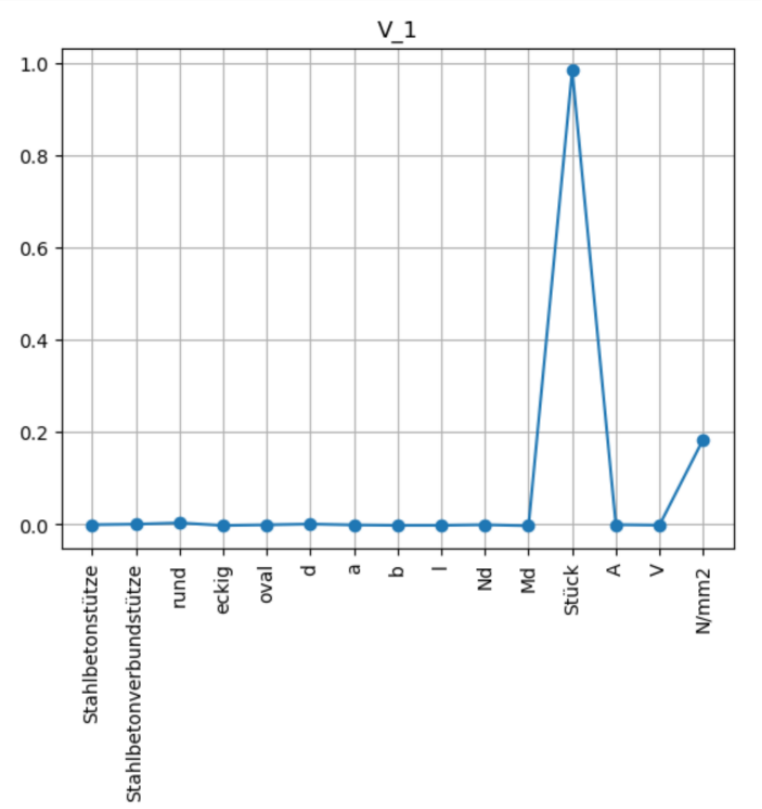
```
df_pca = df.drop(["Datum", "Stückpreis", "Ort", "Projektname", "Bezeichnung", "Einkauf_Baumeister",
                  "Baumeister", "Rabatt inkl. Skonto Baumeister", "Baumeister inkl. Rabatt & Teuerung",
                  "Bemerkungen", "Einkauf_LoMa", "Rabatt inkl. Skonto LoMa", "Teuerung", "Hersteller", "CHF/m3",
                  "LoMa", "Transport", "Total Preis",], axis=1)

df_pca = df_pca.fillna(0, inplace=False)

df_pca = df_pca.replace(to_replace=["x", "X"], value=[1, 1])
```

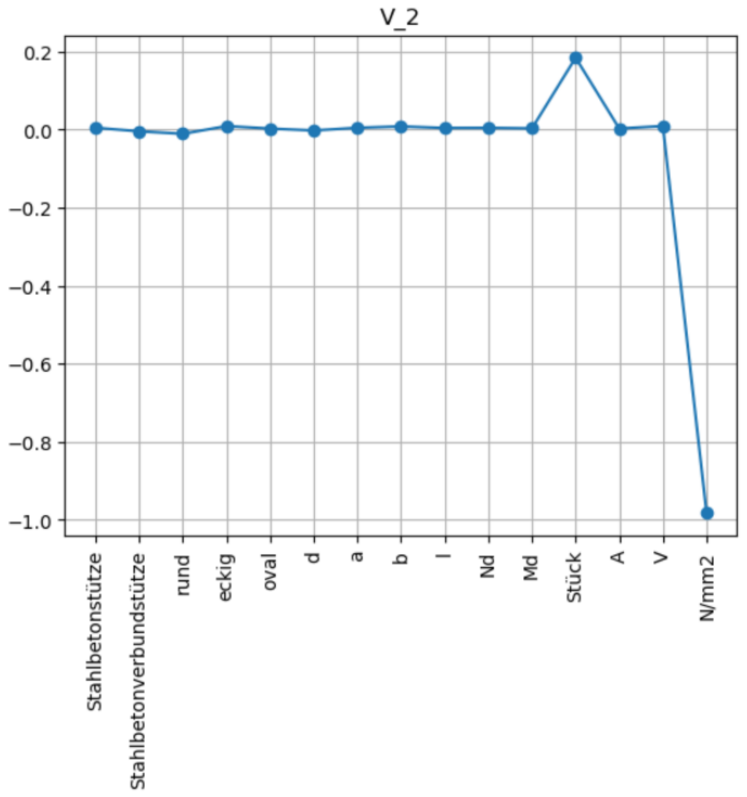
PCA round 2


1.0
0.8
0.6
0.4
0.2
0.0
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14
Principal component

Principal Component Analysis

first 2 components:



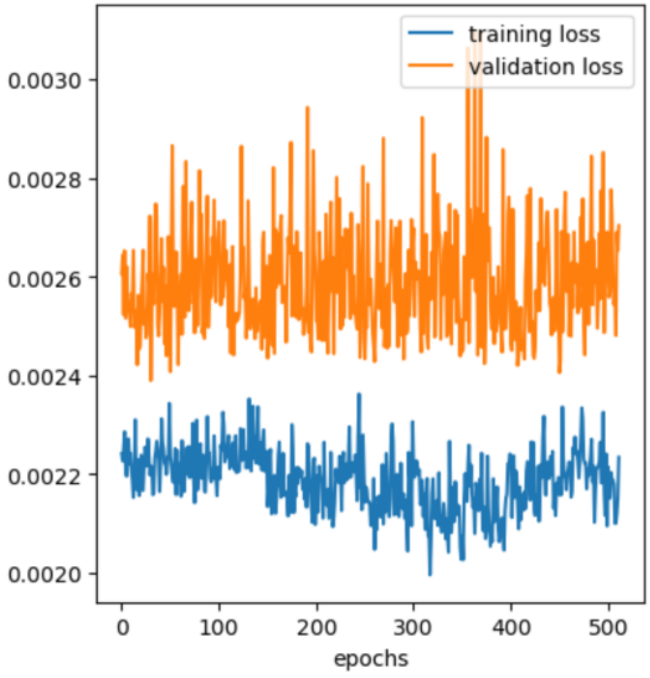


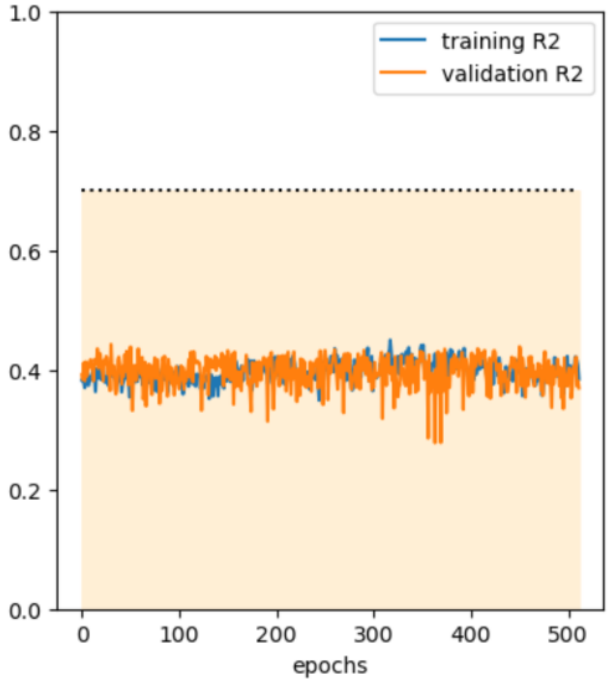
PCA round 2
linear model & neural network

```
1 print(f"{np.sum(pca.explained_variance_ratio_[:2]):0.6f}")
```

```
0.999842
```

```
MSE:
Train: 497
Test: 540

R2:
Train: 0.3197
Test: 0.3200
```






```
22/22 - 0s - loss: 0.0027 - r_square: 0.3697 - 33ms/epoch - 2ms/step
```

PCA round 2 - prediction

```
Stahlbetonstütze = 1
Stahlbetonverbundstütze = 0
rund = 0
eckig = 1
oval = 0
d = 0
a = 0.25
b = 0.25
l = 3.0
Nd = 2000
Md = 0
Stück = 1
# LoMa = 1
# Transport = 10
A = a * b
V = A * l
N_mm2 = Nd*1000/(A*100*100*100)
```

```
1/1 [==============================] - 0s 61ms/step
532
```

Better result even if the accuracy is only around 36%

Conclusion

Conclusion

1. the neural network meets the requirements for accuracy, I can predict the column cost.

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2. test/train split can make a difference

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5. shit in shit out

Conclusion

1. the neural network meets the requirements for accuracy, I can predict the column cost.
2. test/train split can make a difference
3. more data is better
4. the neural network performs better than the linear model
5. shit in shit out
6. know your data