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Using neural networks in a Life & Health insurance context

SAV après-midi, 15 September 2022

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Swiss Re Institute

Key take-aways

- Neural networks should be part of the model toolbox of Life & Health actuaries
- There are plenty of model libraries, tutorials, online courses available – and data availability is also improving
- **Try it out…**

3 examples

Agenda

1. Mortality forecasting
2. Detecting anomalies in mortality rates
3. Neural networks as an alternative to classical survival models

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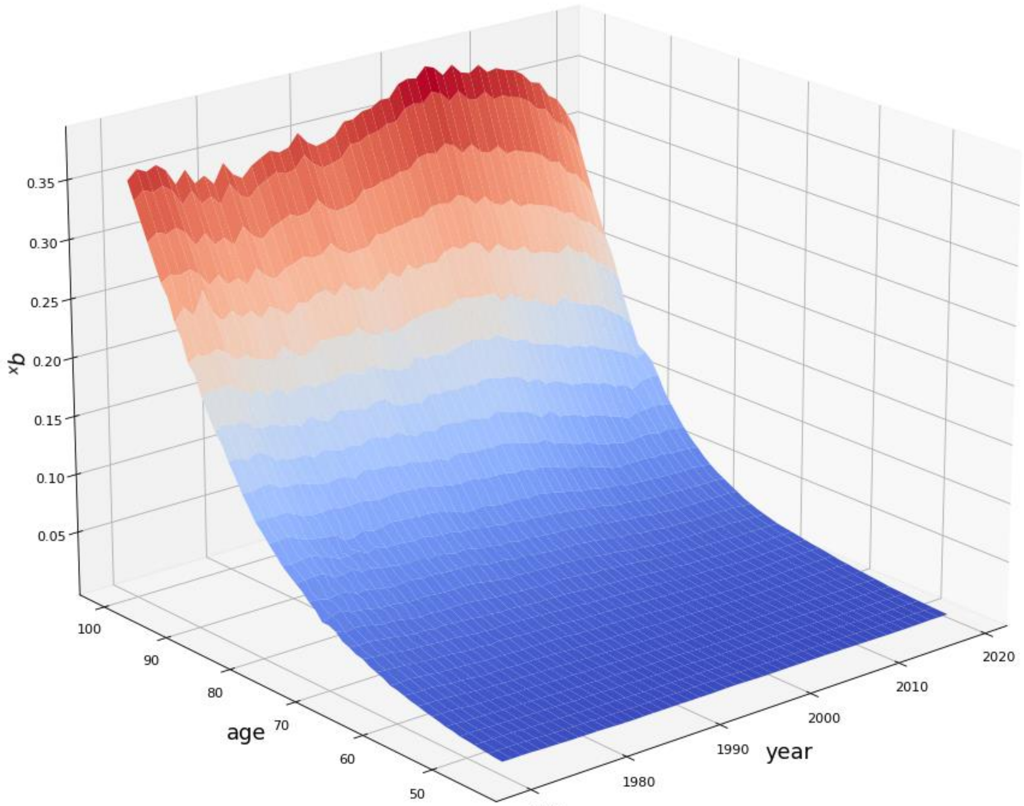
Swiss Actuarial Association
Data Science Working Group
actuarialdatascience.org

Example 1: Mortality forecasting

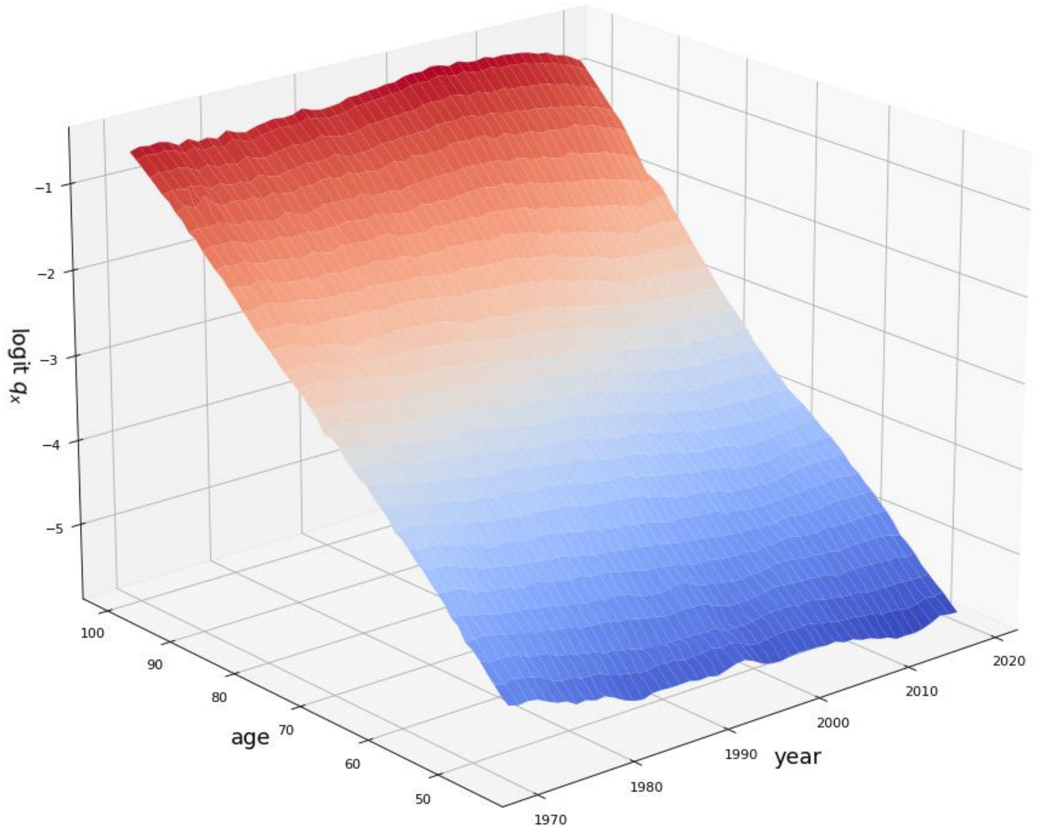
Mortality rates $q_{x,t}$ US males, 1970 to 2019



Data source: mortality.org

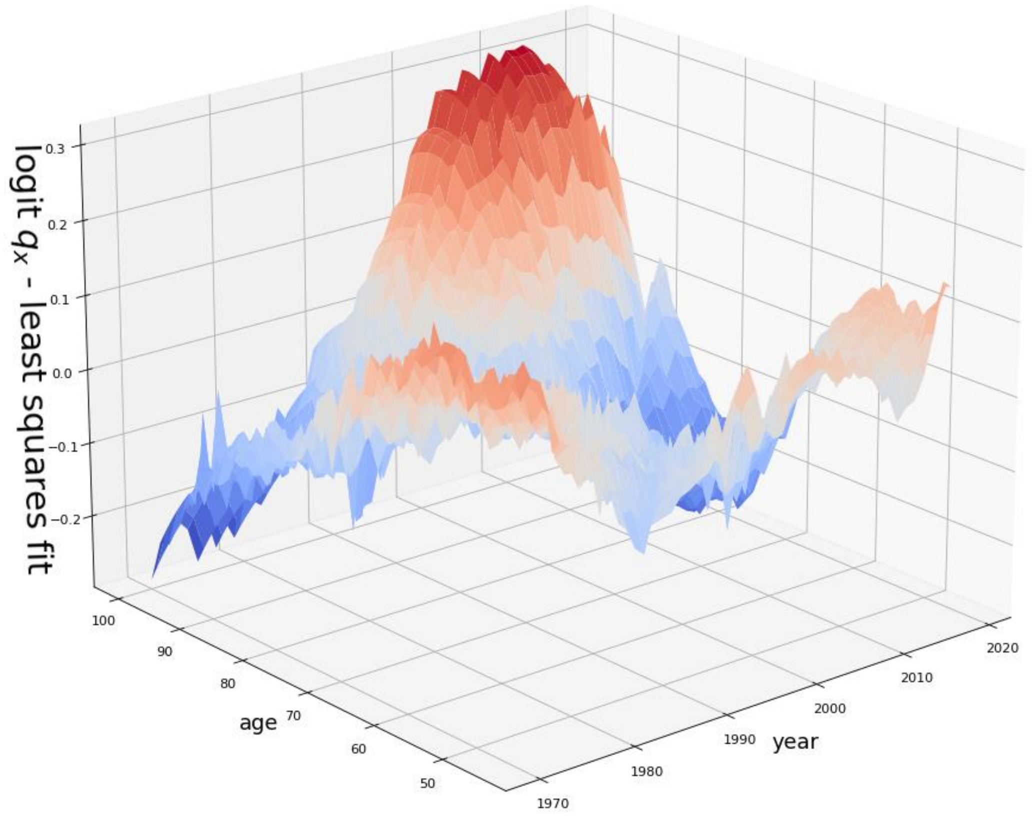
Example 1: Mortality forecasting

logit $q_{x,t}$ US males, 1970 to 2019



Example 1: Mortality forecasting

logit $q_{x,t} - (a_0 + a_1 x + a_2 t)$ based on least squares US males, 1970 to 2019



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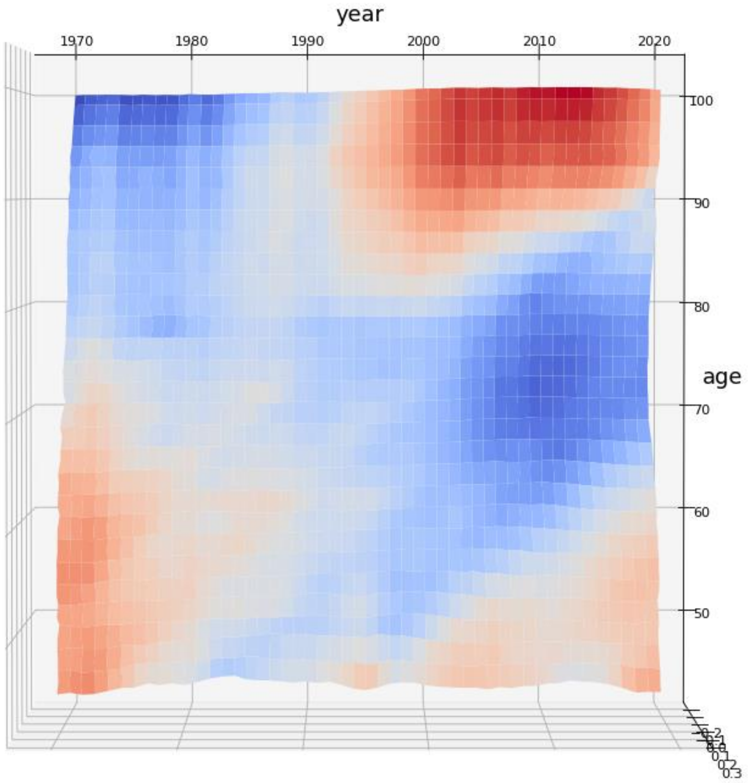

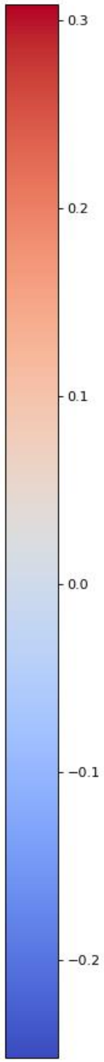

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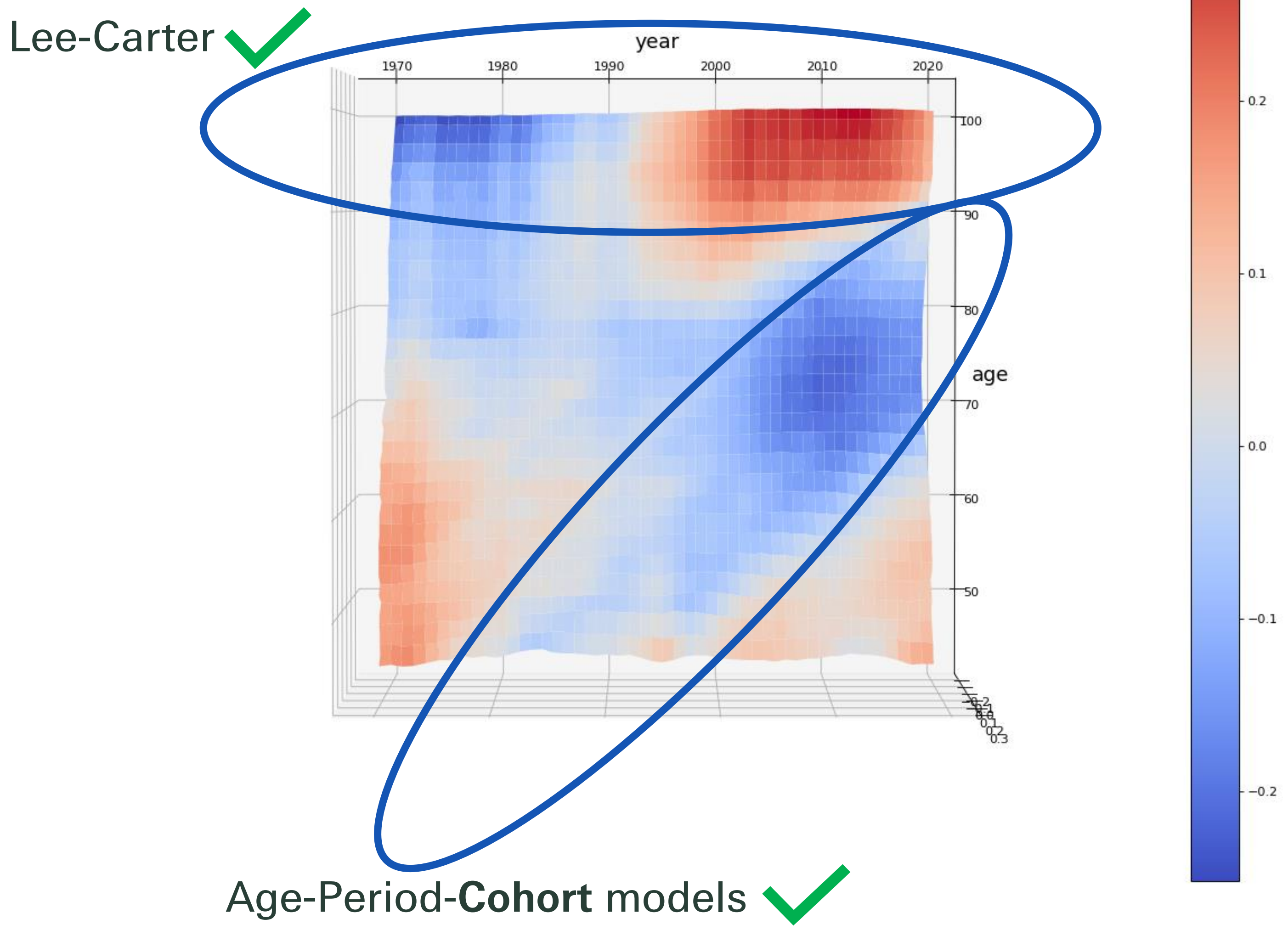

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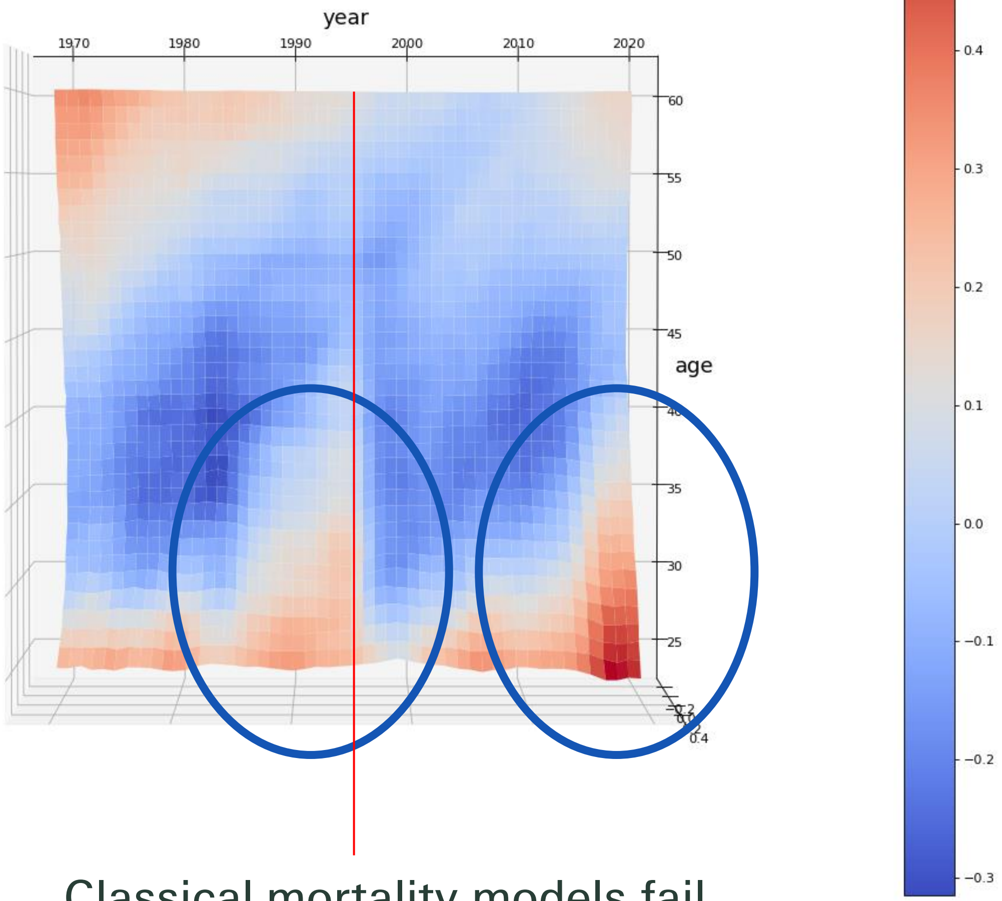
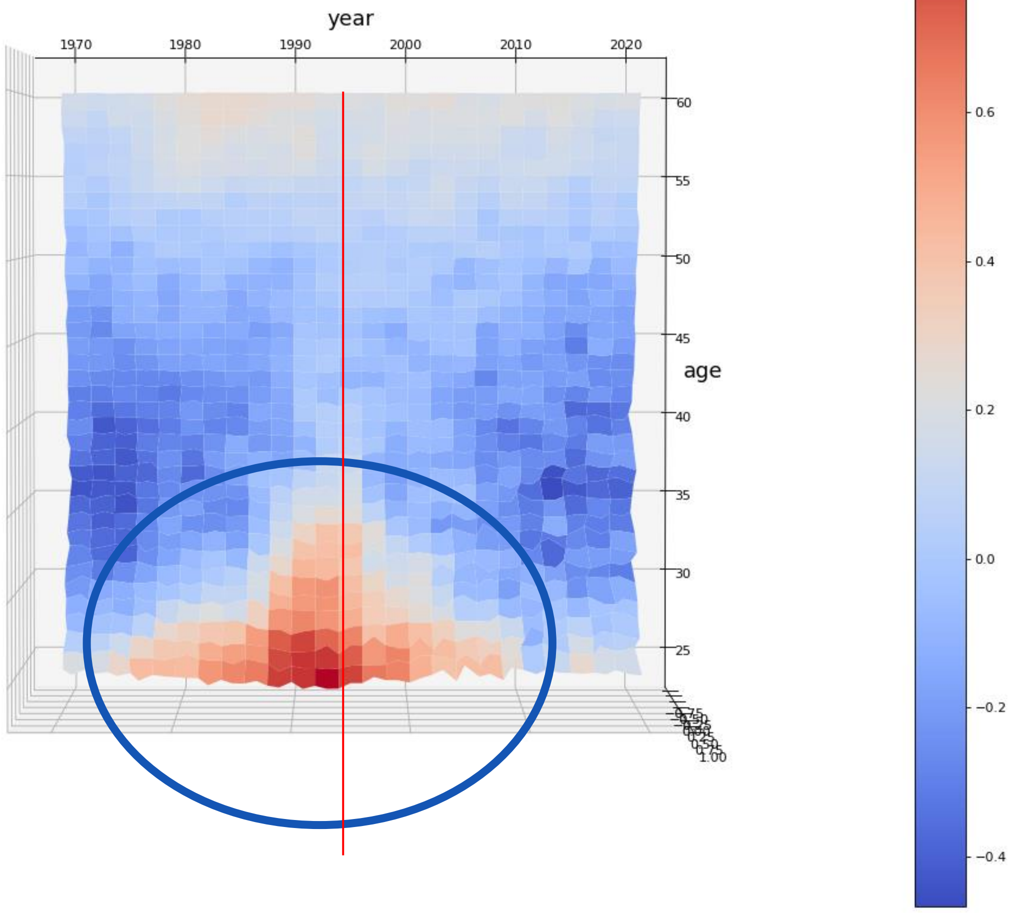
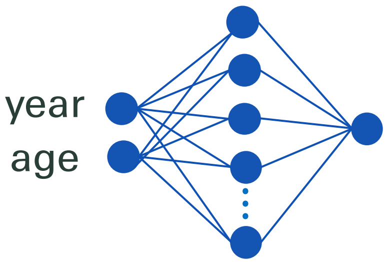


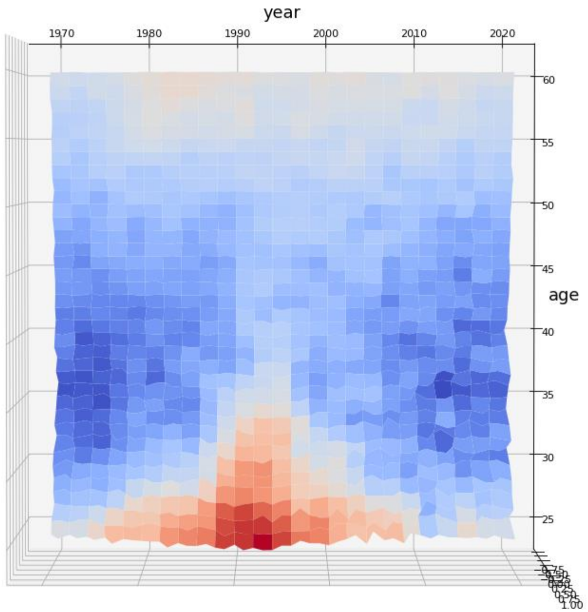
logit $q_{x,t} - (a_0 + a_1 x + a_2 t)$ based on least squares CH males, 1970 to 2019



Classical mortality models fail to capture “local” patterns ❌

Example 1: Mortality forecasting

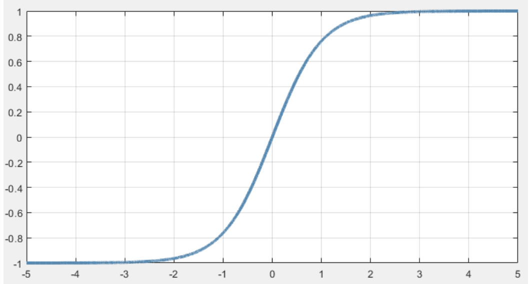




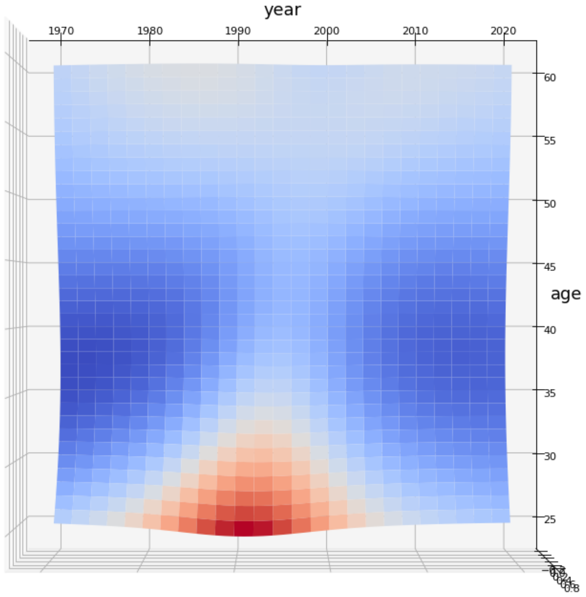

```
from tensorflow import keras

model = Sequential()
model.add(Dense(100))
model.add(Activation('tanh'))
model.add(Dense(1))
model.compile(loss=keras.losses.mean_squared_error)
summary = model.fit(x=X, y=Y, epochs=800, verbose=0, validation_split=0.1)

fit = model.predict(X)
```



Model fitting (no forecasting yet)



Forecasting: See for example case study 6 at actuarialdatascience.org

Example 2: Detecting anomalies in mortality rates

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
46	0.00349	0.00344	0.00329	0.00323	0.00307	0.00308	0.00306	0.00311	0.00323	0.0034
47	0.00384	0.00376	0.00365	0.00349	0.00344	0.00349	0.0034	0.00343	0.00352	0.00359
48	0.00416	0.00412	0.004	0.00399	0.00383	0.00383	0.00376	0.00368	0.00375	0.0039
49	0.00451	0.00441	0.00434	0.00432	0.00424	0.00418	0.00415	0.00405	0.00418	0.00408
50	0.00494	0.00482	0.00478	0.00475	0.0046	0.00461	0.00455	0.00456	0.00453	0.00447
51	0.00547	0.00532	0.00521	0.00518	0.00517	0.0051	0.00502	0.005	0.00499	0.00494
52	0.00586	0.00585	0.00553	0.0056	0.00563	0.00562	0.00556	0.00555	0.0054	0.00552
53	0.00634	0.00643	0.00616	0.00615	0.00611	0.006	0.00601	0.00602	0.00608	0.0059
54	0.00683	0.00684	0.00667	0.00668	0.00652	0.00657	0.00661	0.00662	0.0066	0.00656
55	0.00748	0.00728	0.00708	0.00722	0.00713	0.0071	0.00713	0.00724	0.00726	0.00716

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
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48	0.00416	0.00412	0.004	0.00399	0.00383	0.00383	0.00301	0.00294	0.003	0.00312
49	0.00451	0.00441	0.00434	0.00432	0.00424	0.00418	0.00332	0.00324	0.00334	0.00326
50	0.00494	0.00482	0.00478	0.00475	0.0046	0.00461	0.00455	0.00456	0.00453	0.00447
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53	0.00761	0.00772	0.00739	0.00738	0.00733	0.0072	0.00721	0.00722	0.0073	0.00708
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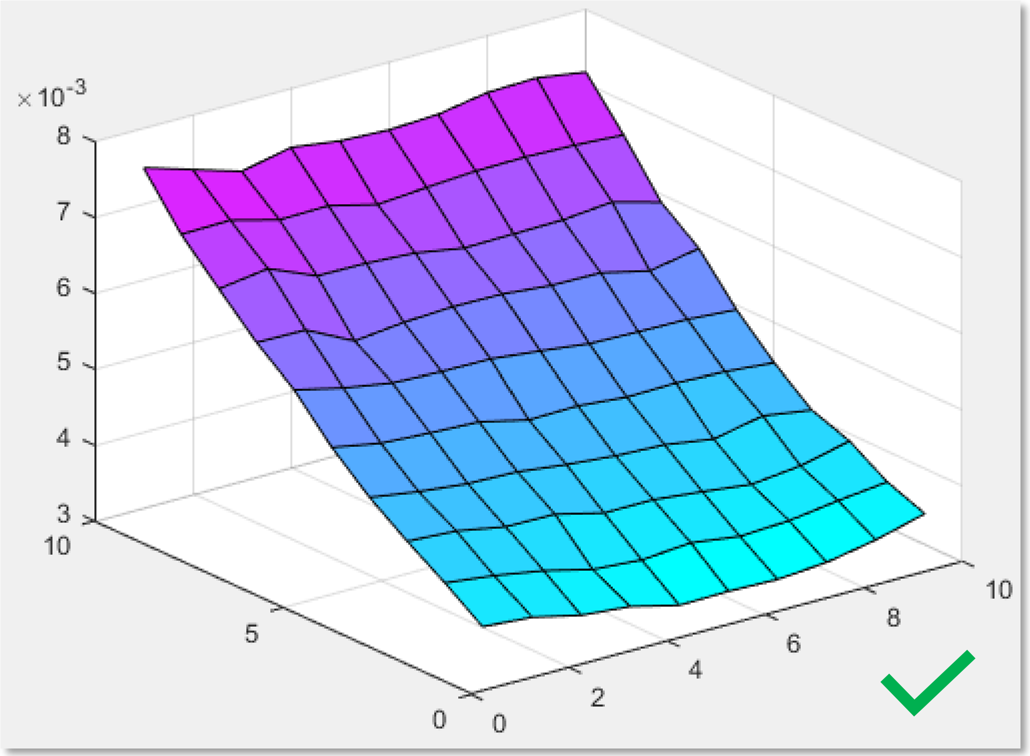
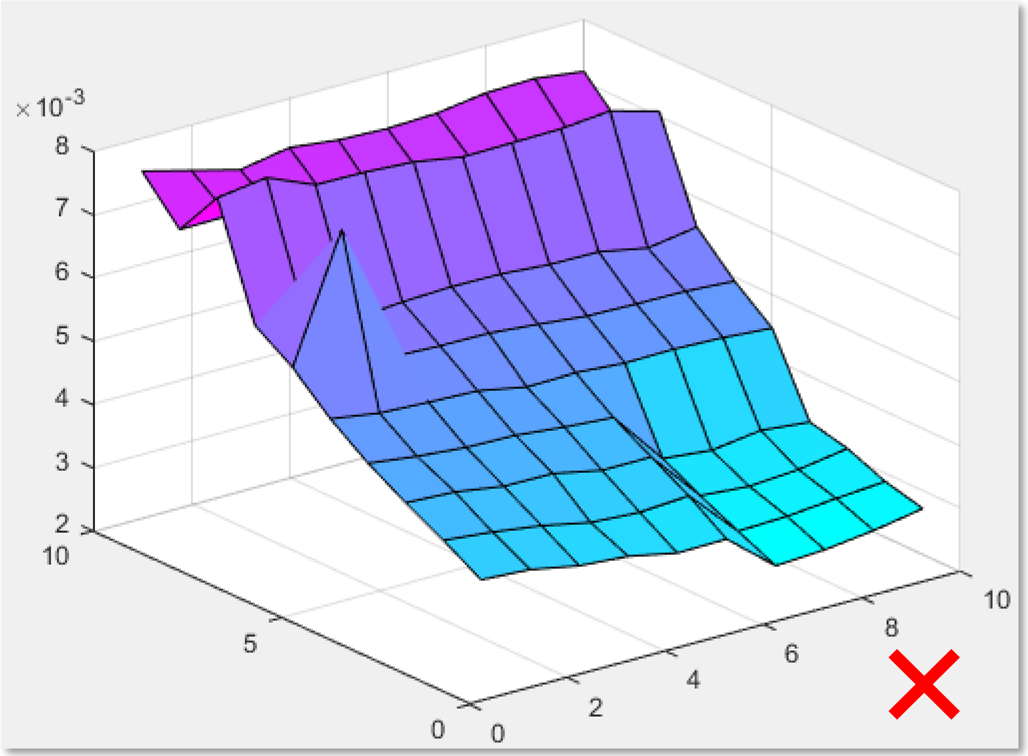
Which of the two subsets of mortality rates have anomalies?

Example 2: Detecting anomalies in mortality rates





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Example 2: Detecting anomalies in mortality rates

Constructing training data: $E_{x+1,t+1} = E_{x,t}(1 - q_{x,t})$

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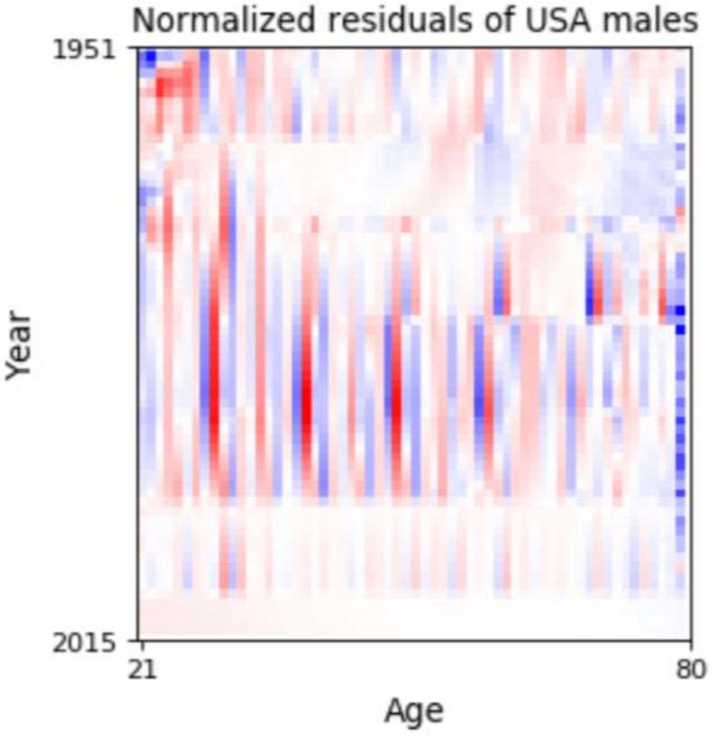
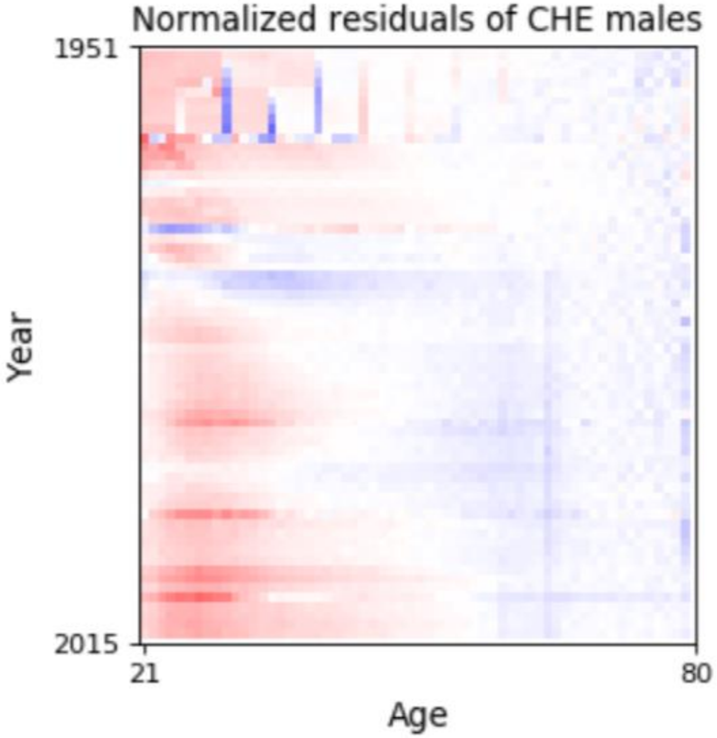
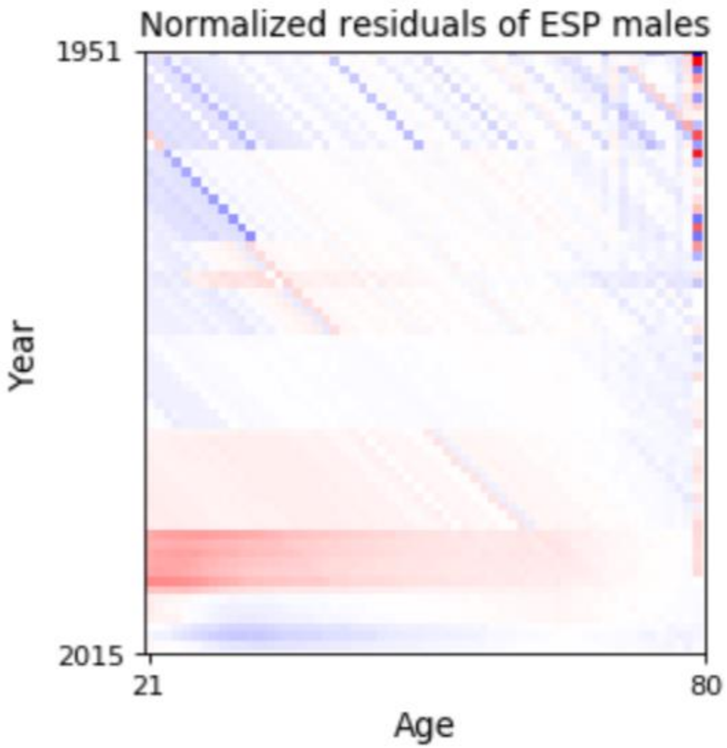




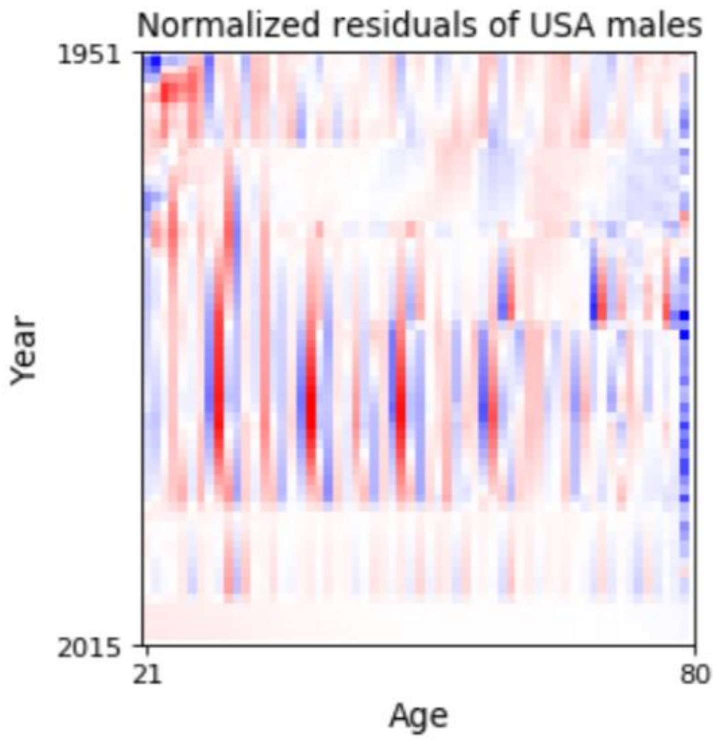


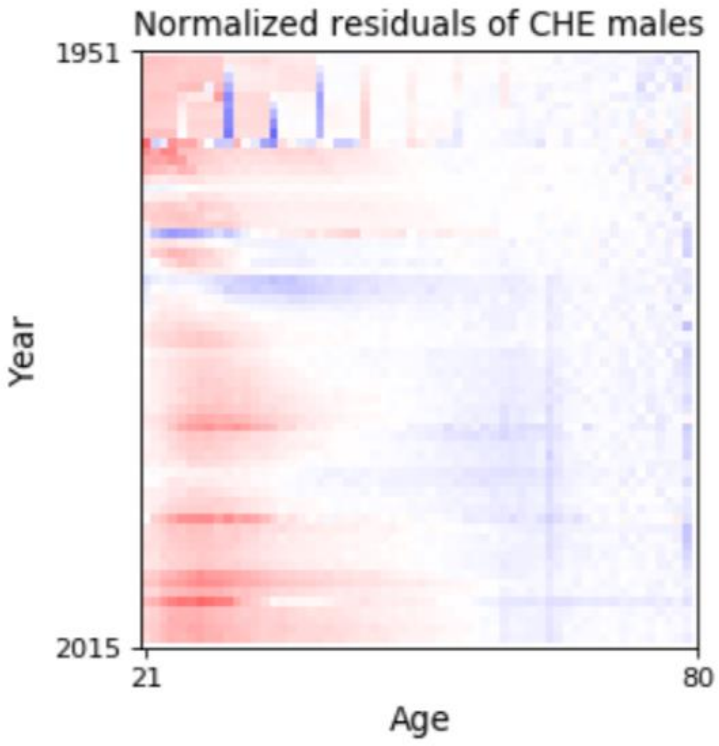
5 year census, groupings, methodologies, errors, migration

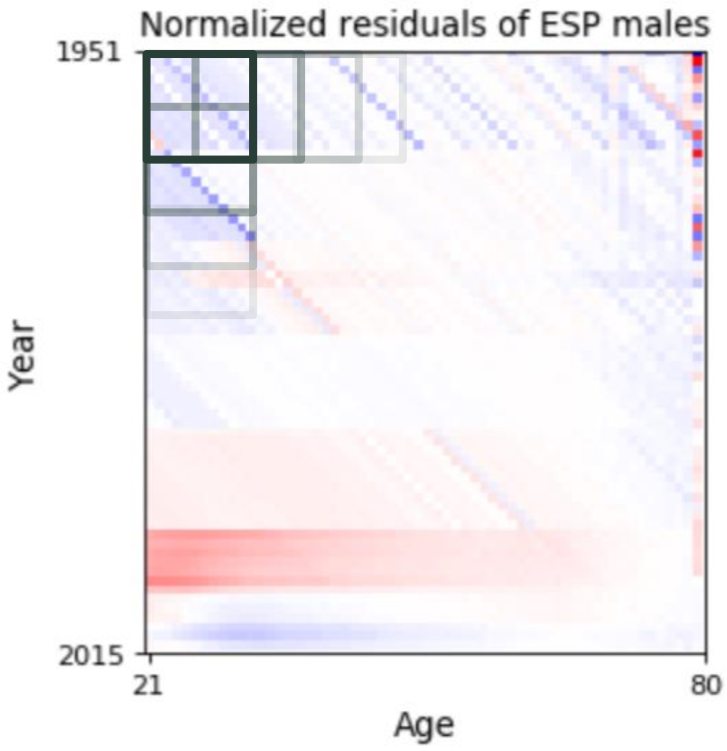
Example 2: Detecting anomalies in mortality rates

Constructing training data: $E_{x+1,t+1} = E_{x,t}(1 - q_{x,t})$

Model input: 10x10 morality rates
Model output/labels: max abs residual







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```
cnn = Sequential()
cnn.add(BatchNormalization())

cnn.add(Conv2D(filters=numberFilters1,
               kernel_size=(filterSize1,filterSize1),
               strides=(1,1),
               padding='valid',
               data_format='channels_last'))
cnn.add(BatchNormalization())
cnn.add(Activation('relu'))

cnn.add(Conv2D(filters=numberFilters2,
               kernel_size=(filterSize2,filterSize2),
               strides=(1,1),
               padding='valid',
               data_format='channels_last'))
cnn.add(BatchNormalization())
cnn.add(Activation('relu'))

cnn.add(Conv2D(filters=numberFilters3,
               kernel_size=(filterSize3,filterSize3),
               strides=(1,1),
               padding='valid',
               data_format='channels_last'))
cnn.add(BatchNormalization())
cnn.add(Activation('relu'))

cnn.add(Flatten())
cnn.add(Dense(1))
cnn.add(Activation('sigmoid'))
cnn.compile(loss='mean_squared_error', optimizer='sgd')
```

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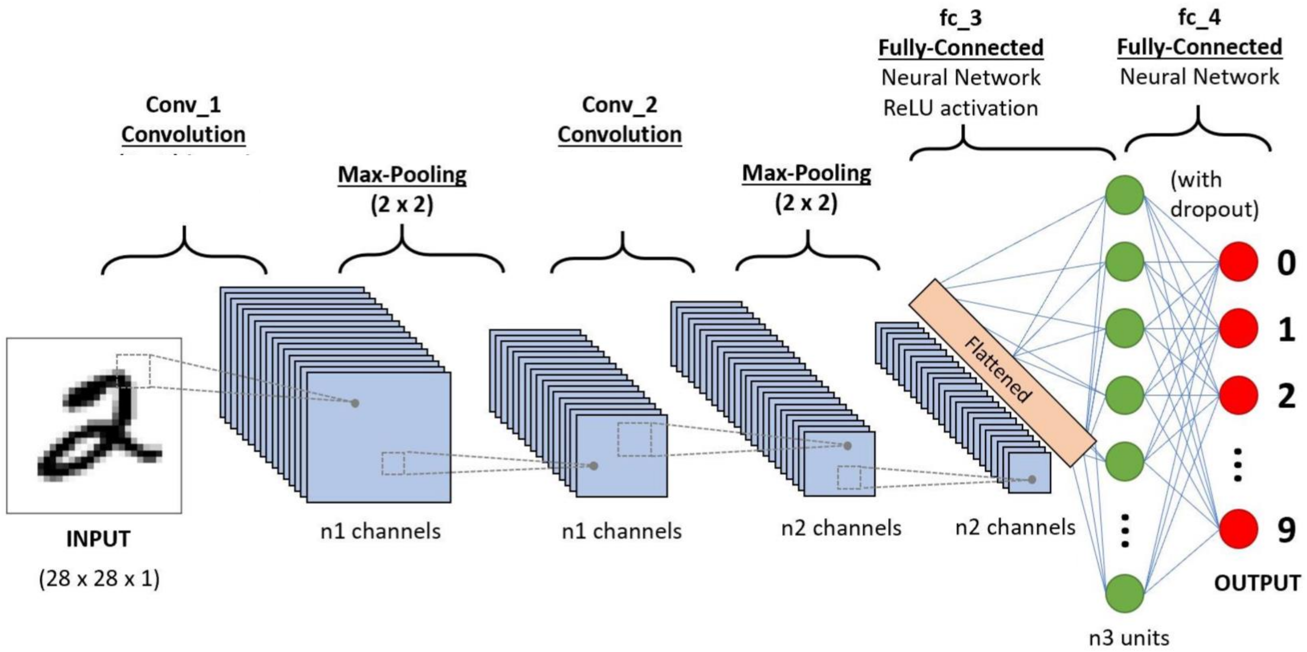
See case study 9 at actuarialdatascience.org

Example 2: Detecting anomalies in mortality rates



MNIST dataset of 70′000 handwritten digits

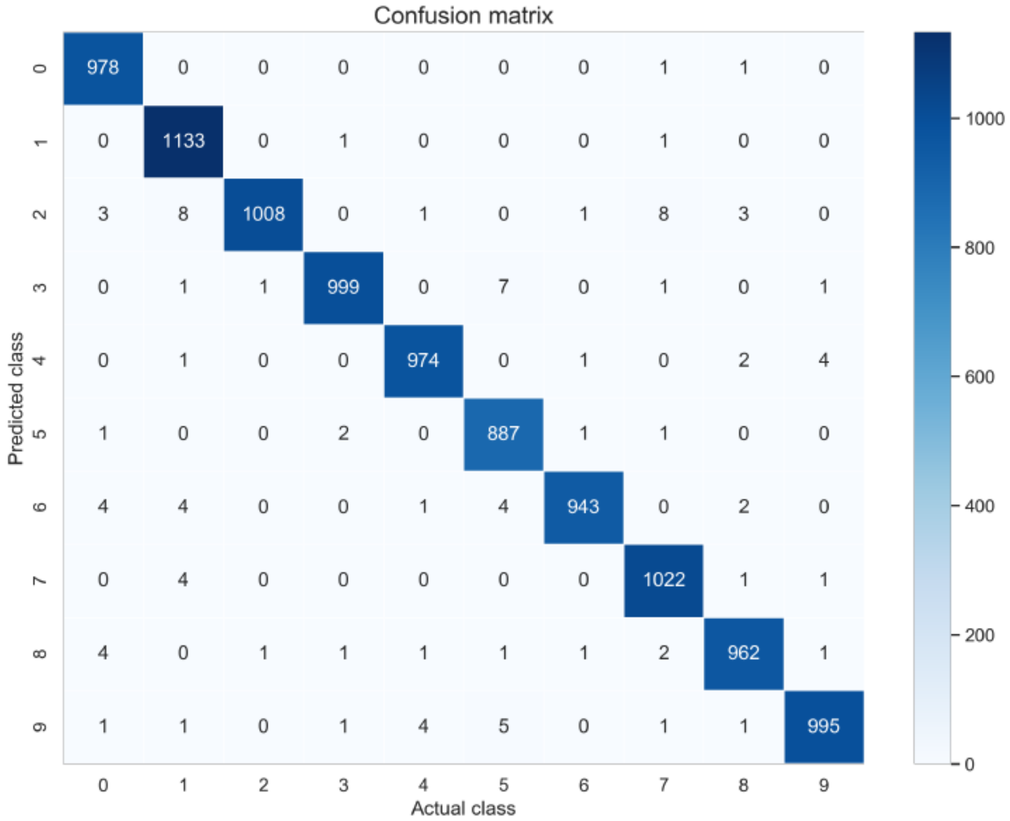
Layer	input size	output size	$f_1^{(k)}, f_2^{(k)}$
1. Conv.	28×28	$26 \times 26 \times 10$	$3, 3$
2. Batch norm.	$26 \times 26 \times 10$	$26 \times 26 \times 10$	–
3. ReLU ϕ	$26 \times 26 \times 10$	$26 \times 26 \times 10$	–
4. Max-pooling	$26 \times 26 \times 10$	$13 \times 13 \times 10$	$2, 2$
5. Conv.	$13 \times 13 \times 10$	$11 \times 11 \times 20$	$3, 3$
6. Batch norm.	$11 \times 11 \times 20$	$11 \times 11 \times 20$	–
7. ReLU ϕ	$11 \times 11 \times 20$	$11 \times 11 \times 20$	–
8. Max-pooling	$11 \times 11 \times 20$	$10 \times 10 \times 20$	$2, 2$
9. Conv.	$10 \times 10 \times 20$	$8 \times 8 \times 40$	$3, 3$
10. Batch norm.	$8 \times 8 \times 40$	$8 \times 8 \times 40$	–
11. ReLU ϕ	$8 \times 8 \times 40$	$8 \times 8 \times 40$	–
12. Max-pooling	$8 \times 8 \times 40$	$4 \times 4 \times 40$	$2, 2$
13. Flatten	$4 \times 4 \times 40$	640×1	–
14. Fully-conn.	640×1	10×1	–
15. Softmax output	10×1	10×1	–

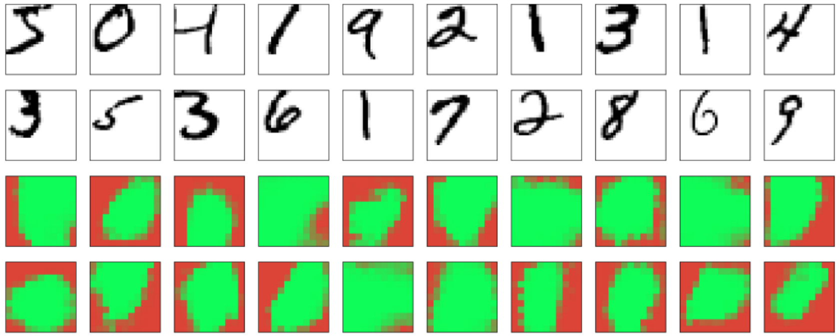
15′710 learnable parameters in total

The convolutional layer in layer *k*, applies:

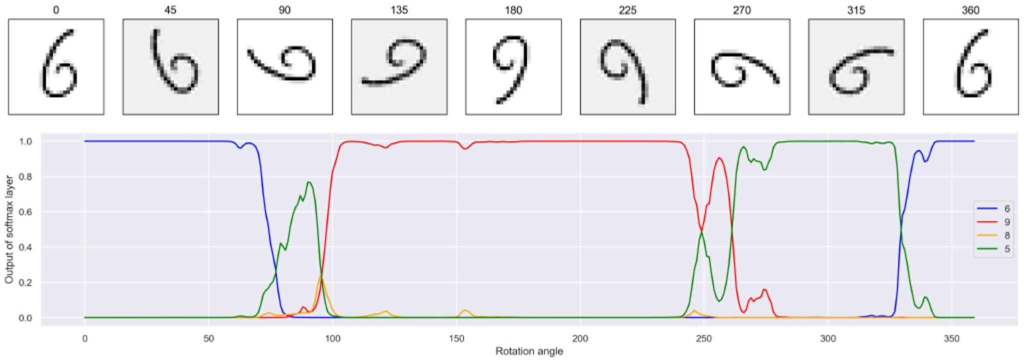
$$\boldsymbol{x} \mapsto z^{(k)}_{i_1,i_2}(\boldsymbol{x}) := w^{(k)}_{0,0} + \sum_{j_1=1}^{f_1^{(k)}} \sum_{j_2=1}^{f_2^{(k)}} w^{(k)}_{j_1,j_2} x_{i_1+j_1-1,i_2+j_2-1}$$

Example 2: Detecting anomalies in mortality rates

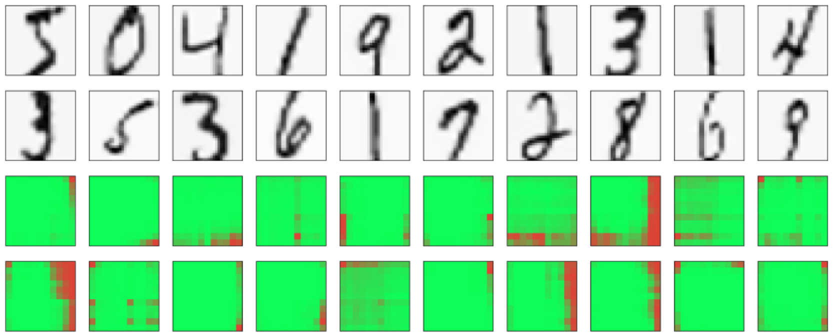




Translation

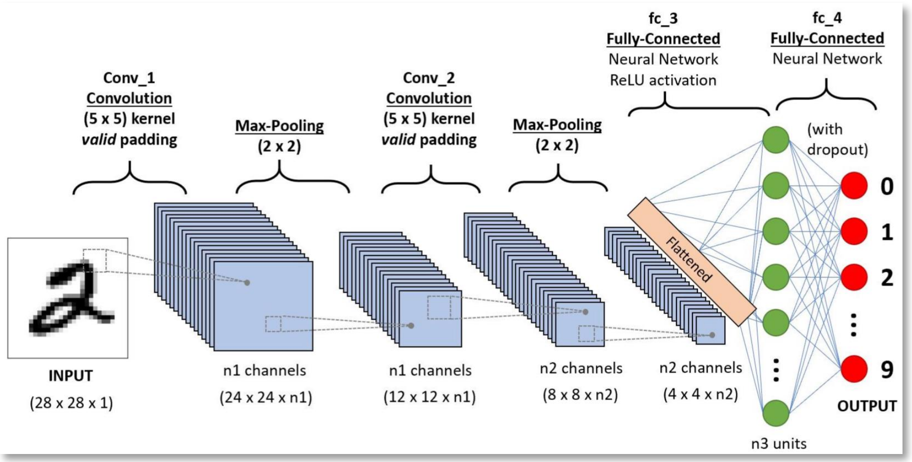


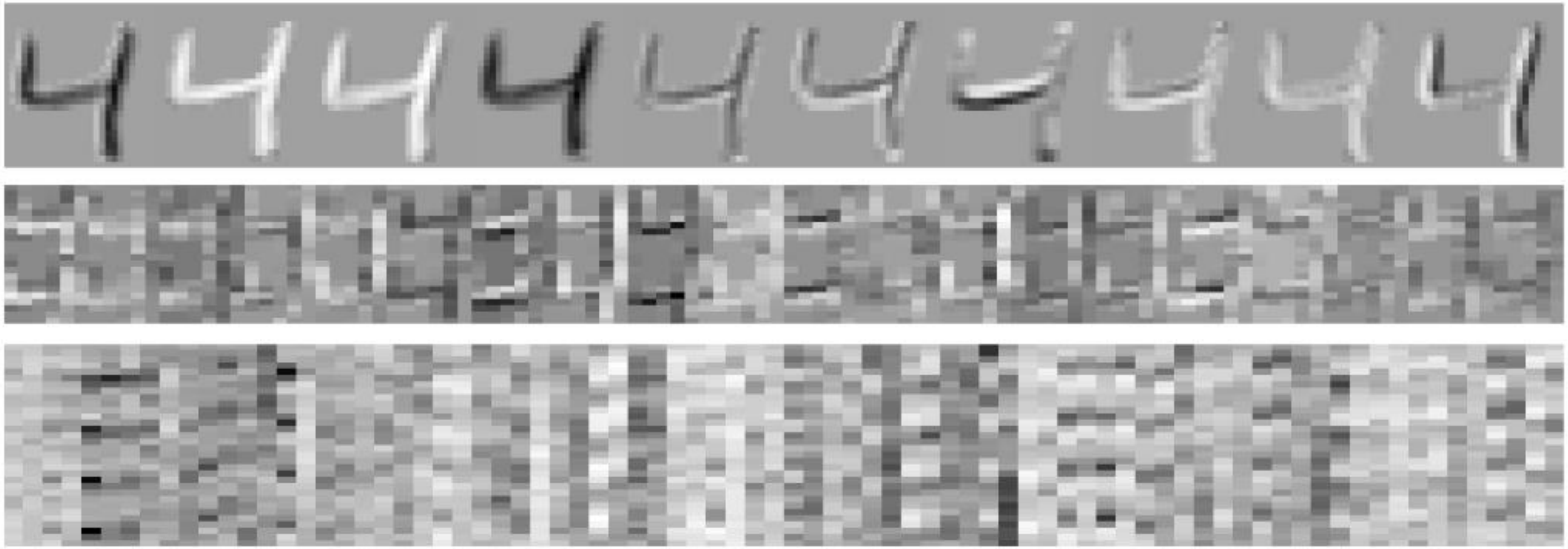
Rotation



Scaling

Example 2: Detecting anomalies in mortality rates





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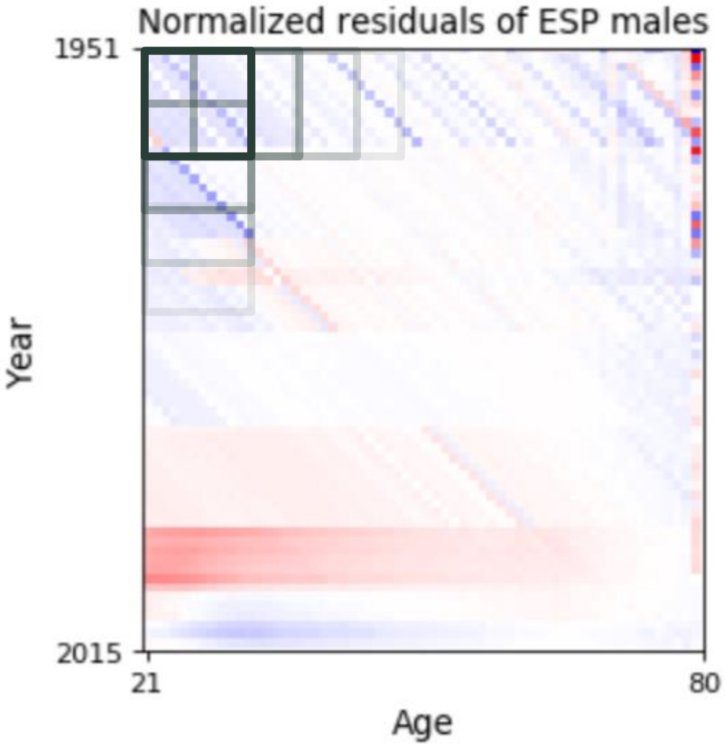
Example 2: Detecting anomalies in mortality rates

Model input: 10x10 morality rates (x males/females/difference)
Model output/labels: max abs residual



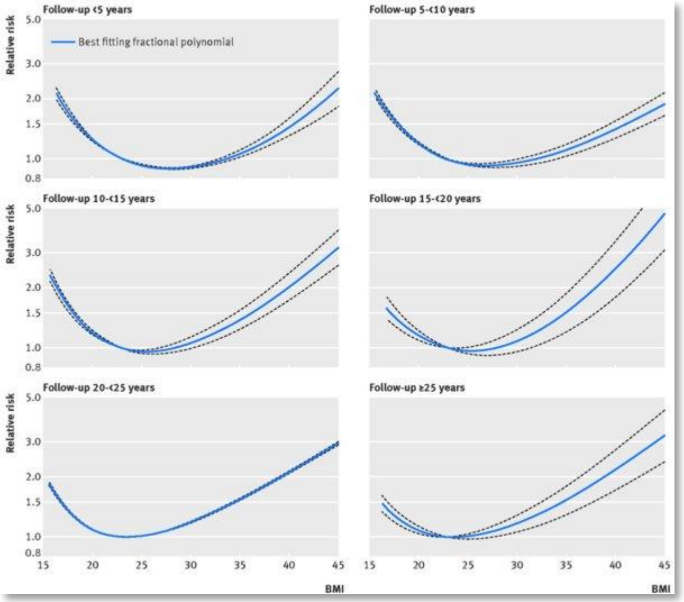
Layer	input size	output size	$f_1^{(k)}, f_2^{(k)}$
1. Batch norm.	$10 \times 10 \times 3$	$10 \times 10 \times 3$	–
2. Conv.	$10 \times 10 \times 3$	$8 \times 8 \times 16$	$3, 3$
3. Batch norm.	$8 \times 8 \times 16$	$8 \times 8 \times 16$	–
4. ReLU ϕ	$8 \times 8 \times 16$	$8 \times 8 \times 16$	–
5. Conv.	$8 \times 8 \times 16$	$6 \times 6 \times 32$	$3, 3$
6. Batch norm.	$6 \times 6 \times 32$	$6 \times 6 \times 32$	–
7. ReLU ϕ	$6 \times 6 \times 32$	$6 \times 6 \times 32$	–
8. Conv.	$6 \times 6 \times 32$	$4 \times 4 \times 64$	$3, 3$
9. Batch norm.	$4 \times 4 \times 64$	$4 \times 4 \times 64$	–
10. ReLU ϕ	$4 \times 4 \times 64$	$4 \times 4 \times 64$	–
11. Flatten	$4 \times 4 \times 64$	$1'024 \times 1$	–
12. Fully-conn.	$1'024 \times 1$	1×1	–
13. Sigmoid output	1×1	1×1	–

24’839 learnable parameters in total

Example 3: Neural networks as an alternative to classical survival models

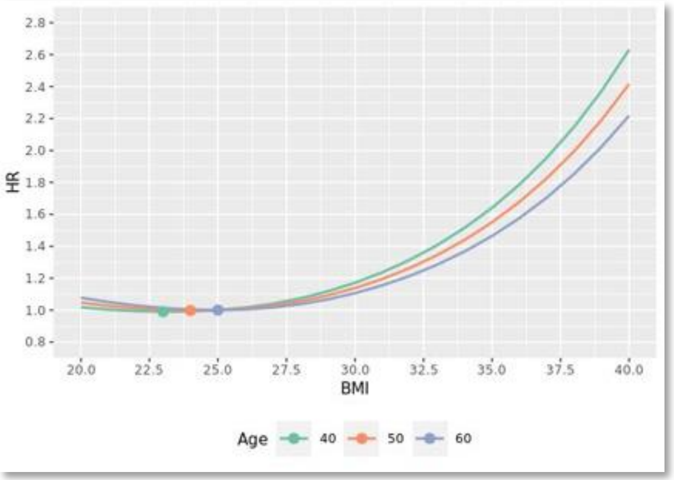
- Develop a **risk score** *r* that takes as inputs
  - individual ***risk factors*** $\boldsymbol{R_i}$ like BMI, blood pressure, step counts, etc. (as well as age *x*, gender *g*),
  - ***insurance product* information *p*** like (e.g. mortality or critical illness, policy duration, regional aspects, etc.), and
  - necessary ***expert judgment D*** on e.g. long-term trends

and as output first derives *relative risk* with respect to mortality/morbidity.



Source: www.bmj.com/content/353/bmj.i2156

$$r_{x,g,p}\colon\ R_1 \times R_2 \times \cdots \times R_n \times D \to (0,\infty)$$



Source: Swiss Re internal project on UK THIN data

dacadoo

Vitality

Milliman IntelliScript®

Swiss Re Life Guide

Commercial risk scores

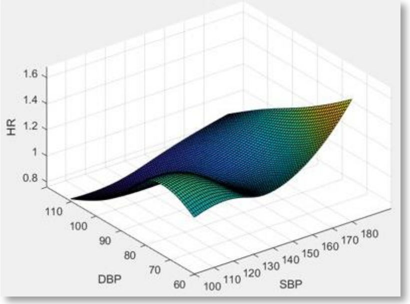
Example 3: Neural networks as an alternative to classical survival models

Large longitudinal datasets

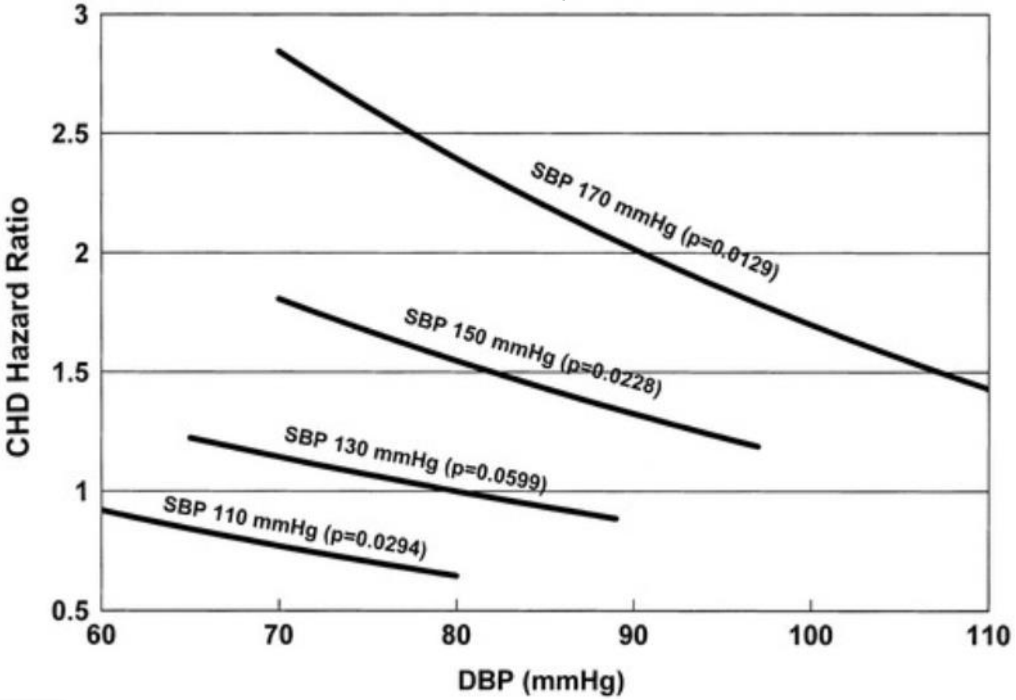
ID	Year	BMI	SBP	DBP	...	Death
1	2005	25	130	84	...	0
1	2006	26	136	88	...	0
1	2007	26	126	82	...	0
1	2008	26	128	84	...	0
1	2009	27	130	82	...	1
2	2007	23	116	70	...	0
2	2008	23	122	74	...	0
...	...	...	...	...	...	...

- Cox proportional hazard model
- Accelerated failure time model

- Recurrent neural networks
- Convolutional neural networks



Hazard ratios, relative risk



What's in from this for L&H insurance?

Understanding the dependencies and interactions between various mortality/morbidity drivers for underwriting and pricing.

Is Pulse Pressure Useful in Predicting Risk for Coronary Heart Disease?
The Framingham Heart Study
Stanley S. Franklin. Shehzad A. Khan, Nathan D. Wong, Martin G. Larson and Daniel Levy
https://doi.org/10.1161/01.CIR.100.4.354, Circulation. 1999;100:354–360

Key take-aways

- Neural networks should be part of the model toolbox of Life & Health actuaries
- There are plenty of model libraries, tutorials, online courses available – and data availability is also improving
- **Try it out...**

3 examples

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Thank you!
Any questions?

Contact us

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