Results Presentation

Team: PandeML



Outline

- 1) Chosen Approaches
 - a) Parametric Curve Fitting
 - b) Linear Regression
 - c) SIR
 - d) LSTM
- 2) Comparison of Models
- 3) Conclusion



Idea: Number of infected/deceased/recovered people will follow a

Logistic Curve.

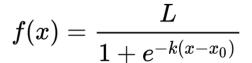
→ Fit data to a such a curve using scipy's

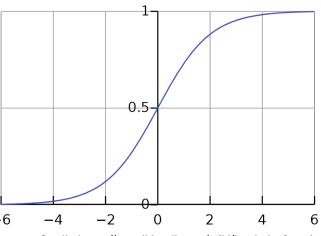
optimize.curve_fit

Parameters: L := Maximal value

k := Logistic growth rate

 $x_0:=$ Midpoint





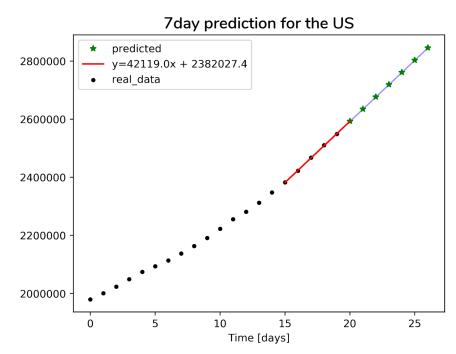
Credit: https://en.wikipedia.org/wiki/Logistic_function

Linear Regression

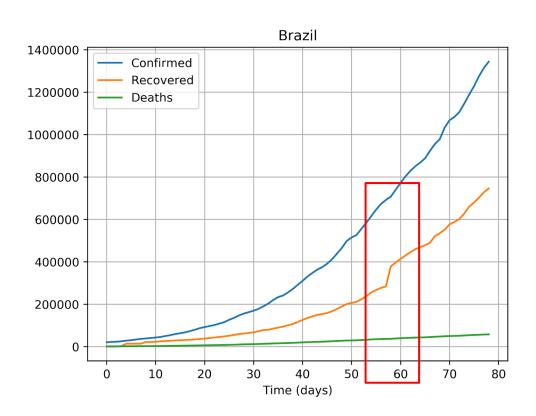
- **Motivation**: Simpler models tend to perform better for short time predictions
- Model: Ordinary least squares linear regression:

$$\min_{\boldsymbol{w}\in\mathbb{R}^p}||\boldsymbol{X}\boldsymbol{w}-\boldsymbol{y}||_2^2=\min_{\boldsymbol{w}\in\mathbb{R}^p}\sum_{i=1}^n(\boldsymbol{w}^{\mathsf{T}}\boldsymbol{x}^{(i)}-y_i)^2.$$

- Parameters: LinReg of last 5 days for both 2day and
 7day prediction
- Usage of scipy.stats.linregress, to determine: slope, intercept and std_err
- 95%-Confidence-Interval via: 1.96*std_err
- Pros: Mathematically straightforward, Transparent
- Cons: Not capable to predict complex relationships (in opposite e.g. SIR)



Linear Regression



SIRD

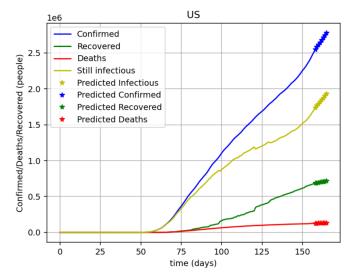
$$\begin{aligned} \frac{dS}{dt} &= -\beta \cdot I \cdot \frac{S}{N} \\ \frac{dI}{dt} &= -(1 - \alpha) \cdot \gamma \cdot I - \alpha \cdot \rho \cdot I \\ \frac{dR}{dt} &= (1 - \alpha) \cdot \gamma \cdot I \\ \frac{dD}{dt} &= \alpha \cdot \rho \cdot I \end{aligned}$$

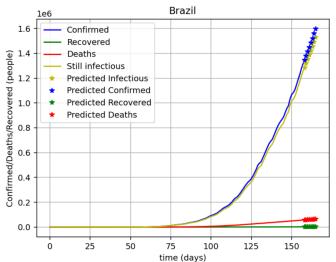
- \triangleright β = number of persons an infected person infects per day
- days = number of days an infected person is infectious
- ightharpoonup R = beta imes days = total number of persons an infected person infects

Problem:

- SIR-model tries to describe "real" epidemic outbreak, but prediction is made for incomplete data (mainly missing recovered data) → parameters need to be calculated from given data → leads to unreal parameters
- Example:
 - Calculated parameters for prediction in US:

R = 7.13,
$$\beta$$
 = 0.018, days = 396.8





LSTM-Recursive NN

LongShortTermMemory

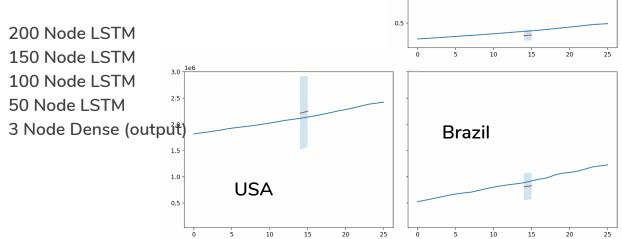
Α Α

India

2.5 -

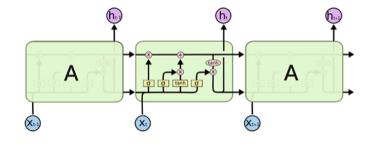
1.5

Idea: Use COVID19 data from all countries world wide to learn the behavior 166 (11000 training Samples, 2000 Samples for validation) Strategy: Multiple Parallel Input and Multi-Step Output for 100 epochs **Input**: 7 Days of data (Cases, Deaths, Recovered) Output: 2 or 7 Days of Data (Cases, Deaths, Recovered) Architechture:





LongShortTermMemory



2.5 -

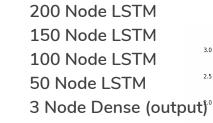
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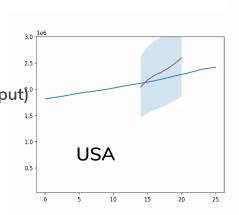
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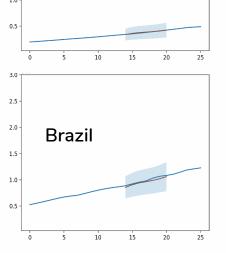
Input: 7 Days of data (Cases, Deaths, Recovered)

Output: 2 or 7 Days of Data (Cases, Deaths, Recovered)

Architechture:

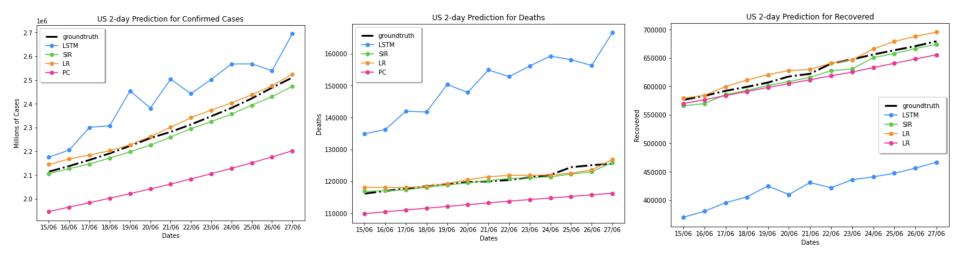




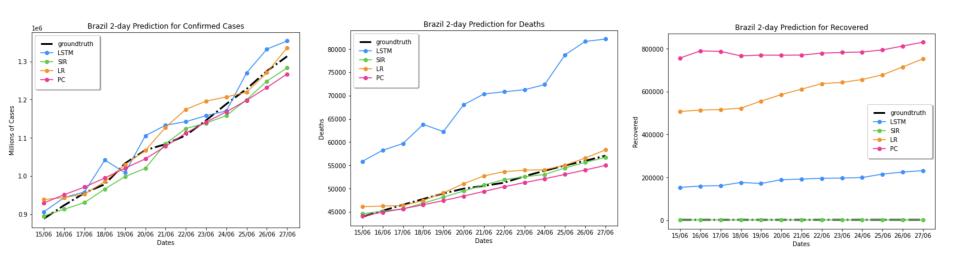


India

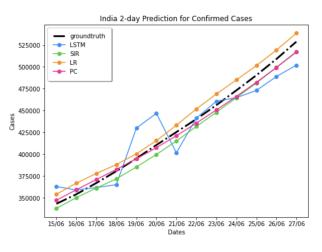
2-day Predictions: US

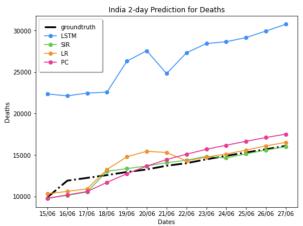


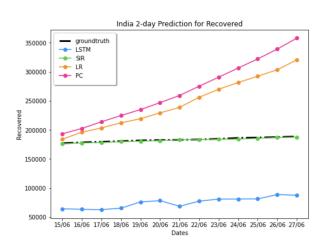
2-day Predictions: Brazil













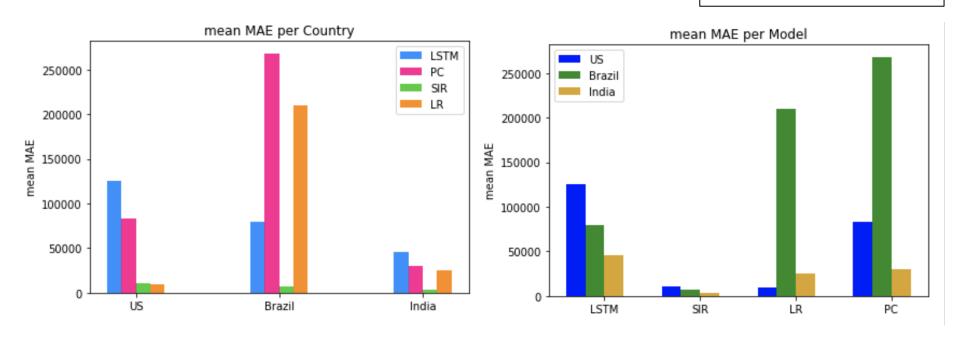
Mean Absolute Error:

n 33 *

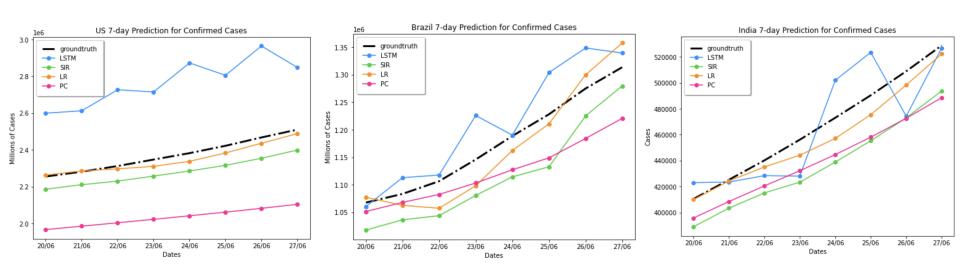
(<u>abs</u>(# predicted cases - # actual cases)

abs(# predicted deaths - # actual deaths)

<u>abs(# predicted recovered - # actual recovered)</u>)



7-day Predictions





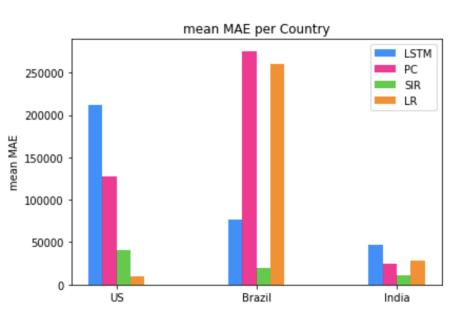
Mean Absolute Error:

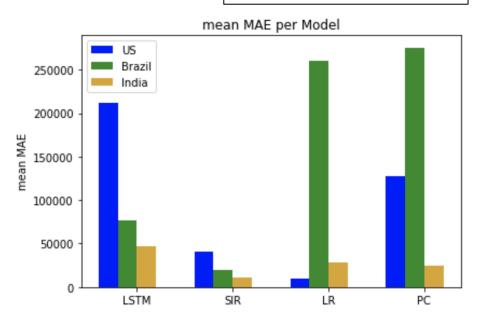
33 *

(\underline{abs} (# predicted cases - # actual cases)

 \underline{abs} (# predicted deaths - # actual deaths)

<u>abs</u>(# predicted recovered - # actual recovered))





Conclusion

Learnings:

- SIRD-model best <u>estimate</u> covid-19 BUT may <u>lose interpretability</u>
- LSTM with multiple outputs need well prepared training data
- Some 7day models may be more accurate for 2day predictions
- Complex models have a lot <u>more effort</u> to get robust results.