Estimating the Effect of Social Distancing Interventions

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• Data science connection with Memphis Fire Department

• Model COVID hospitalization/fatalities as quickly as possible
Imperial College London (ICL) Model

• Semi-mechanistic Bayesian hierarchical model of interventions
  • Self isolating if ill
  • Social distancing encouraged
  • Schools or universities closing
  • Sport banned (= public gatherings of more than 1000)
  • Public events banned (= public gatherings of more than 100 participants)
  • Lockdown

Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe

What are mechanistic models?

\[
\frac{dS}{dt} = -\frac{\beta IS}{N},
\]

\[
\frac{dI}{dt} = \frac{\beta IS}{N} - \gamma I,
\]

\[
\frac{dR}{dt} = \gamma I,
\]
How is the ICL model different

• Mechanistic concepts implemented in Bayesian framework
  • **Death counts** are negative binomial distributed and their expectation is a function of infections on previous days
  • **Number infected** modeled as a discrete renewal process that accounts for population saturation
  • Death counts linked to number infected based on country-level infection fatality ratio and distribution of times from infection to death

• Model assumes intervention effect is the same everywhere and instantaneous
  • Allows pooling of effects across countries
Estimated intervention effects for Tennessee

Interventions:
- Complete lockdown
- Large gatherings banned
- School closure
- Self isolation
- Social distancing

Rt

0.0 0.5 1.0 1.5 2.0

2 Mar 9 Mar 16 Mar 23 Mar 30 Mar 6 Apr 13 Apr 20 Apr 27 Apr

50% 95%
Estimated intervention effects for U.S.

<table>
<thead>
<tr>
<th>Intervention</th>
<th>Mean</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>LL</td>
</tr>
<tr>
<td>Self isolating if ill</td>
<td>.012</td>
<td>.059</td>
</tr>
<tr>
<td>Sport</td>
<td>.021</td>
<td>.102</td>
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<tr>
<td>Social distancing encouraged</td>
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<td>Public events</td>
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<td>.379</td>
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<tr>
<td>Schools or universities closing</td>
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<td>.518</td>
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<tr>
<td>Lockdown</td>
<td>.785</td>
<td>.987</td>
</tr>
</tbody>
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Abbreviations: CI, confidence interval; LL, lower limit; UL, upper limit
Lockdown effects on $R_t$ across states

- No state had an $R_t$ below 1.0 before lockdown
  - $R_t$ of 1.0 means each infected infects one other

- After lockdown, 29 states had an $R_t$ below 1.0
  - Since only 43 states implemented lockdown, that’s 67%

- In these 29 states, lockdown appears to be the critical intervention that allowed containment
Model validity

• Predicted deaths 14 days into the future

• 72% of states had deaths within the confidence interval of the model’s predictions

• Predicted deaths were noticeably higher than actual for Connecticut, New Jersey, Massachusetts, and New York

• The mean absolute error of mean predicted deaths was 50.80, and without these four states the mean absolute error was 10.08.
Limitations

• Interventions may have different effects in different places

• Interventions defined with arbitrary caps (e.g. gatherings of 100)

• Interventions unlikely to have perfect compliance, so not binary

• Ideally, we’d measure effect of interventions on true distancing, and then measure true distancing’s effect on COVID
Collaborators

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• Juliette Unwin, Imperial College London
• Fridtjof Thomas, UTHSC
• Saunak Sen, UTHSC