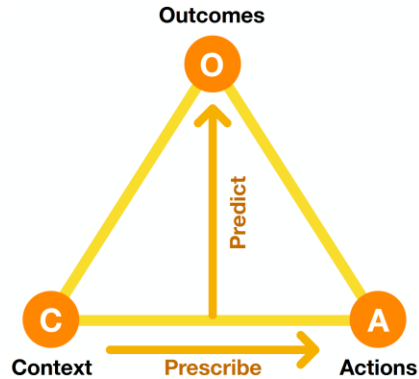


Pandemic Resilience Use Case



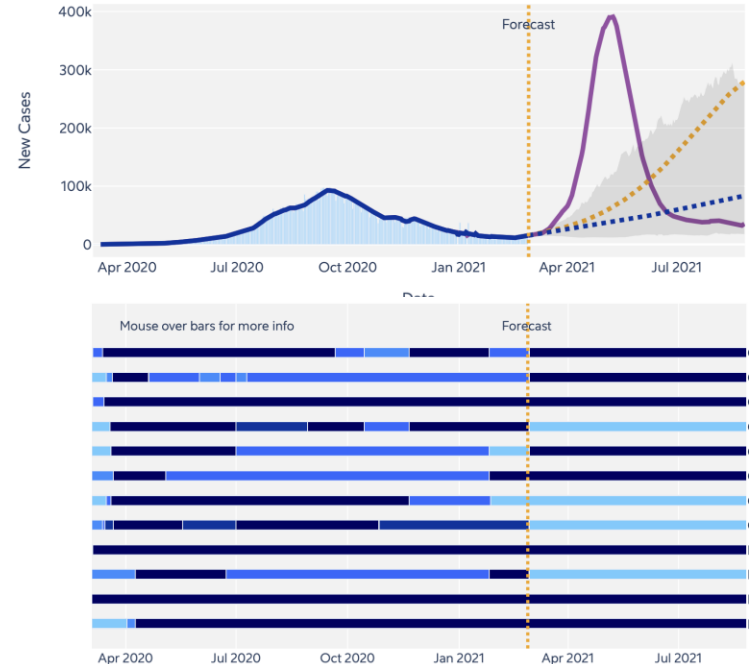
Developed at Cognizant AI Labs 2020-2022

- Risto Miikkulainen, Elliot Meyerson, Olivier Francon, Elisa Canzani, Darren Sargent, Babak Hodjat

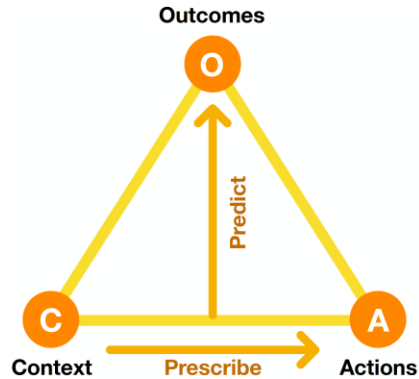
Extended to an XPRIZE competition 2020-2021

- With Amir Banifatemi, Haneen Khalaf, Andrew Tauhert...

Motivation for Project Resilience



A data-driven approach to COVID-19 modeling



Based on two models:

1. A predictive model

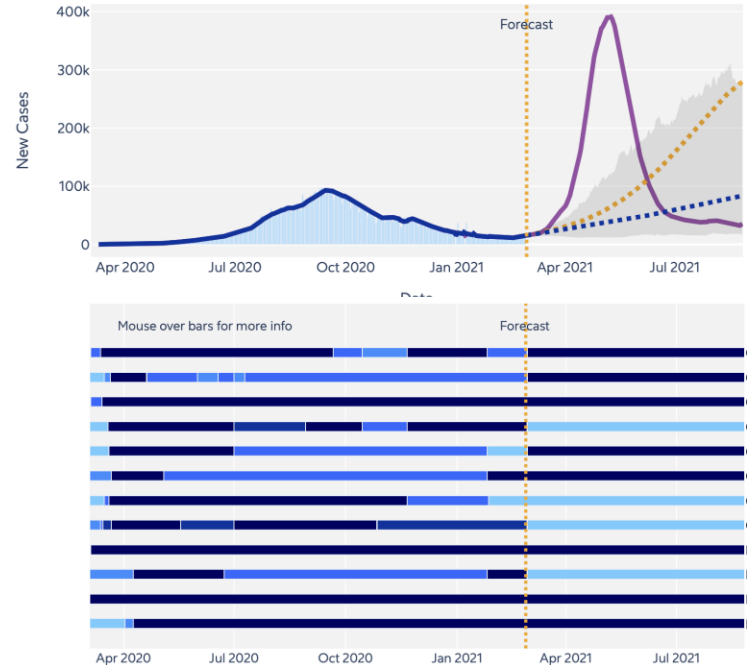
- Given a history of cases and NPIs
- Predict number of cases daily

2. A prescriptive model

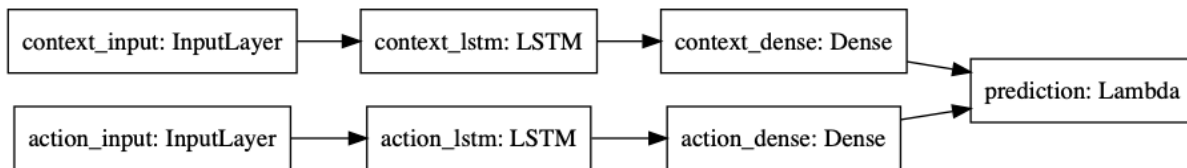
- Given a history of cases and NPIs
- Prescribe NPIs daily

The predictive model is a surrogate for the world

- Makes it possible to evaluate prescriptor candidates



First build a predictor with available data



SEIR, network, agent-based models do not work well as a surrogate

- Too slow: need to create millions of predictions daily
- Too specific: hundreds of countries, millions of NPI settings

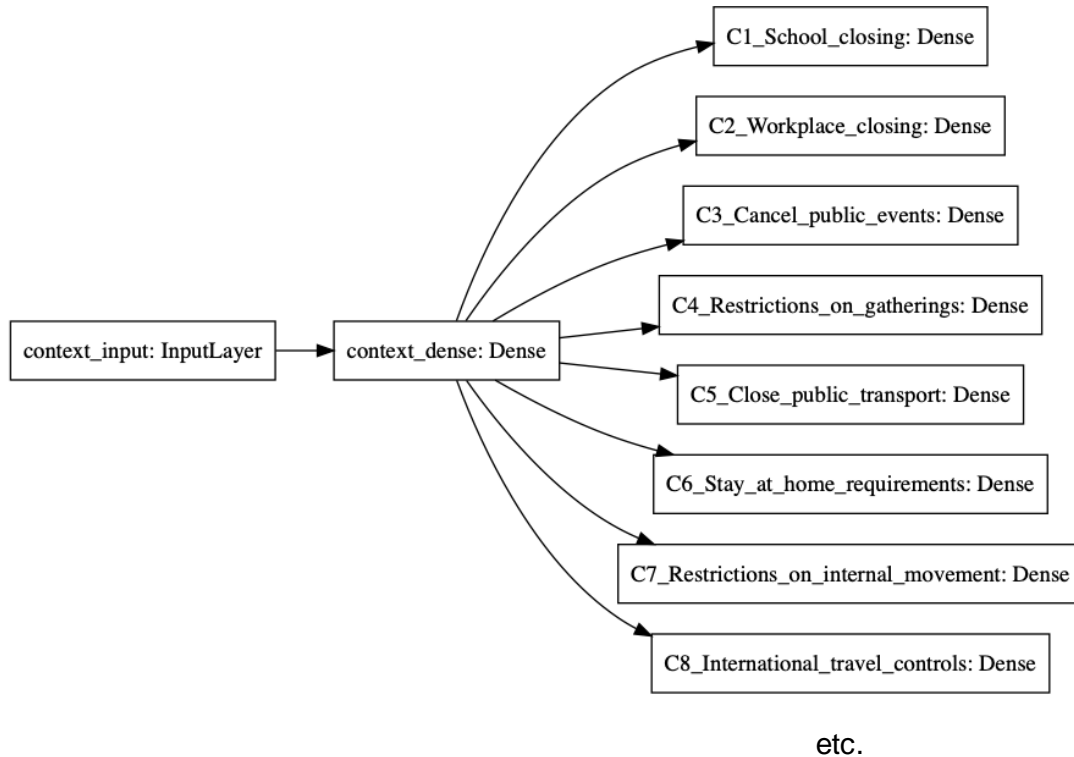
Instead, train a neural network with historical data

- Maps cases and NPIs directly to predictions
- Phenomenological model: Requires no estimation of epidemiological parameters
- Data includes all interactions between parameters! (if enough good data)

Such data was available for COVID19

- Oxford COVID-19 Government Response Tracker (Toby!)
- Daily case numbers and NPIs for most countries

Then evolve a Prescriptor with the Predictor as a surrogate



No gradients!

- Need to search for a good model

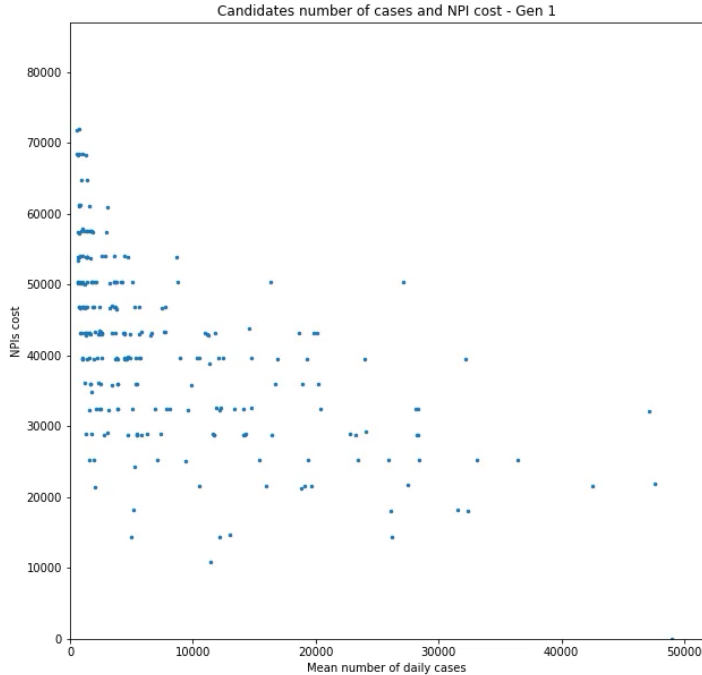
Evolve neural network prescriptors

- Population-based search
- Use Predictor to evaluate each one

Multiobjective

- Minimize future cases
- Minimize stringency of NPIs
(a proxy for economic cost)

Solutions represent different tradeoffs



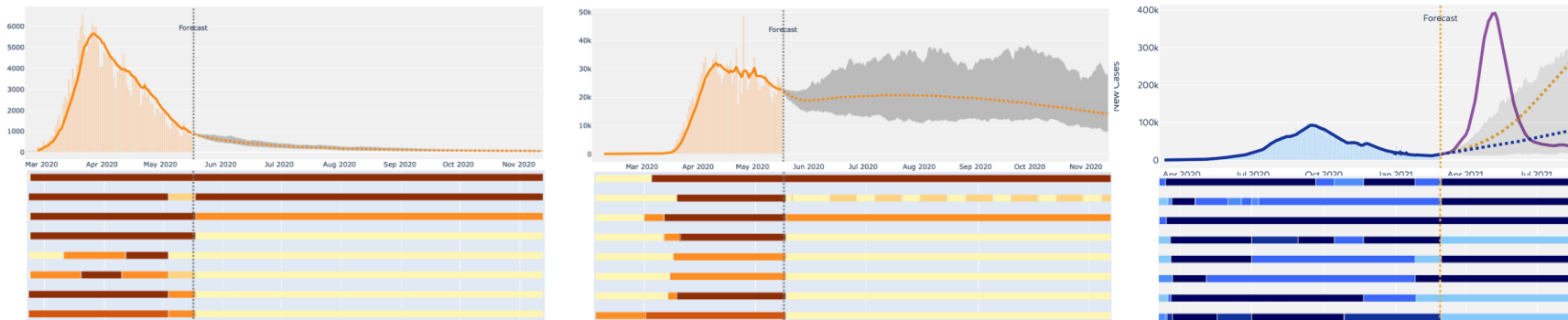
Evolution minimizes both objectives

Results in a Pareto front:

- Some minimize cases
- Some minimize cost
- Others balance the two to different degrees

Given a desired balance, best possible solutions

Discoveries on Prediction and Prescription



Highlights (often 2 weeks in advance):

- May 2020: Focus on schools and workplaces (i.e. indoors); alternation
- Sept 2020: Focus on gatherings, travel restrictions; open schools
- Delta surge: India (March 2021); others with low rates (July 2021)
- August 2021: Recommendations for schools (Iceland)
- Dec 2021: Missed omicron surge; it happened everywhere at once
- March 2022: Impact of masking

Evolutionary AI Decision Making Evolution, New Deep Learning Expert Discussions Software Publications

AI-based Intervention Recommendations for COVID-19

This demo illustrates the non-pharmaceutical interventions (NPIs) that the AI generates for different countries and regions over time, and their predicted effect. You first select country/region from the map at right, and then select the degree to which you'd like to minimize the number of cases vs. minimize the stringency of NPIs from the slider on the left. Among the ~1000 possible NPIs (schedules for the next 90 days), the AI will then recommend one that implements that 'tradeoff' with as few cases and NPIs as possible. The predicted number of cases and the recommended NPIs will be shown over time in the charts below. **NEW:** You can also go back in time with 'counterfactuals', and edit recommendations with 'Custom NPIs'.

See [Outlining COVID-19 interventions](#) for the general context, [in-depth topics](#) for the technical details, and [ESP Introduction](#) for the Evolutionary AI technology and its other applications. See also the [2020 Pandemic Response Challenge](#) (and its [technical details](#)) for a recent machine learning competition inspired by this demo.

Interactive Demo

<https://evolution.ml/demos/npidashboard>

Updated daily May 2020 – Dec 2022

Can be used to obtain data-based recommendations

- Select country
- Select date (current, or past)
- Select health/economy tradeoff (cases vs. NPIs)
- Obtain NPI recommendations and case predictions

Trustworthiness:

- Obtain confidence bounds
- Design custom NPIs with a scratchpad
- Evolve explainable rulesets (instead of neural networks)

Obtaining Recommendations

Select

- Country
- Date (current/past)
- Tradeoff

Country / Region ⓘ

India x ▼

Forecast Options

Current NPIs maintained ⓘ

All NPIs maxed out

All NPIs lifted

Custom NPIs ⓘ Edit

Counterfactuals ⓘ Date

"Today" marker

"Forecast" start marker

Confidence bounds ⓘ

Prescriptor Trade-off: ⓘ

Minimize Cases | | Minimize NPIs

Observe cases

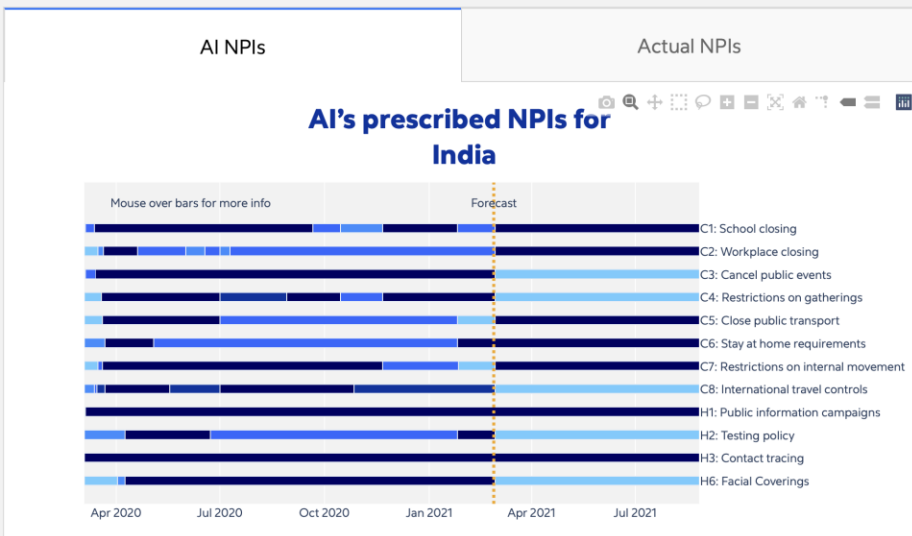
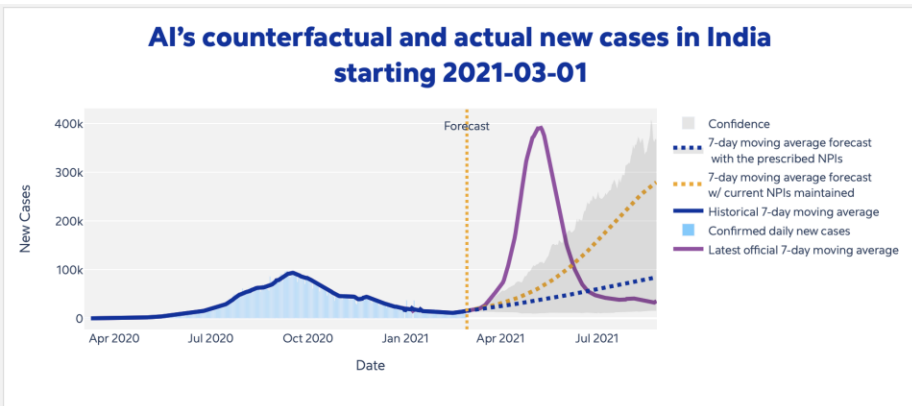
- Actual
- With current NPIs
- With AI NPIs

And confidence bounds

- GP model
- Multiple rollouts

Observe NPIs

- Actual
- Prescribed



Explore alternative NPIs

Start from

- AI's prescriptions
- Current
- Maxed-out
- No NPIs

For instance

- Less school, work, home, transport
- More masks, tests, internatl. travel

Observe results

- A different way to achieve the same result?
- Not quite ☹️

Custom NPIs

Select one of the preset prescriptions and adjust each NPI by clicking on the stringency slider.

Presets

Select...

C1_School closing

C2_Workplace closing

C3_Cancel public events

C4_Restrictions on gatherings

C5_Close public transport

C6_Stay at home requirements

C7_Restrictions on internal movement

C8_International travel controls

H1_Public information campaigns

H2_Testing policy

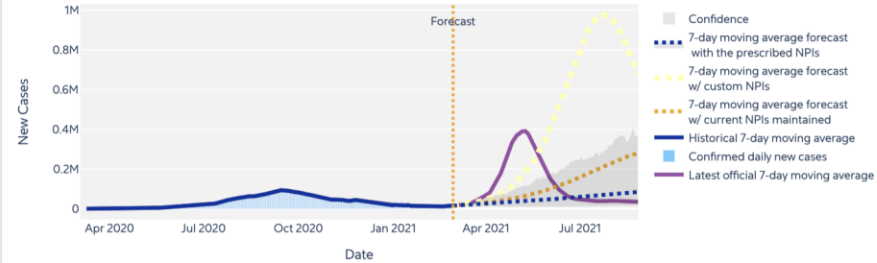
H3_Contact tracing

H6_Facial Coverings

CANCEL

APPLY

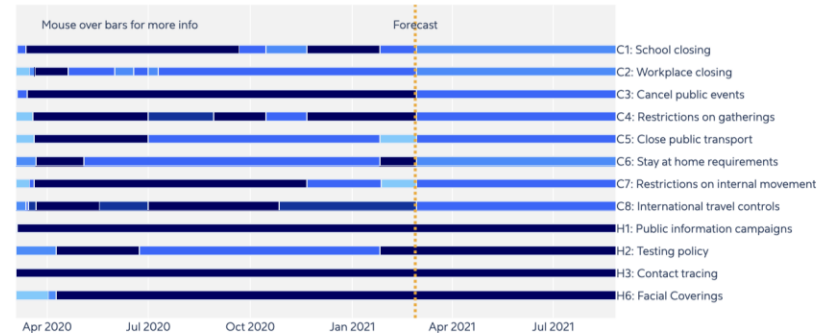
AI's counterfactual and actual new cases in India starting 2021-03-01



Custom NPIs

Actual NPIs

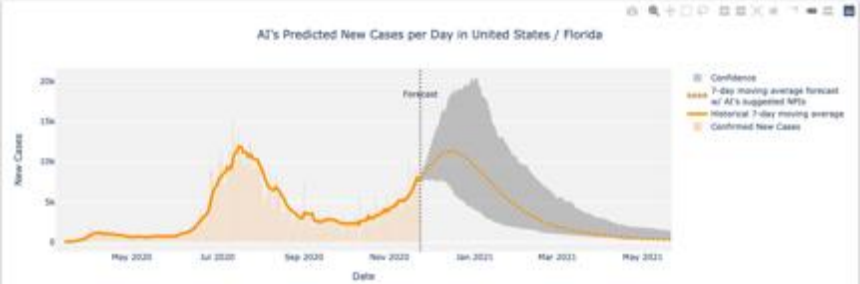
Custom NPIs for India



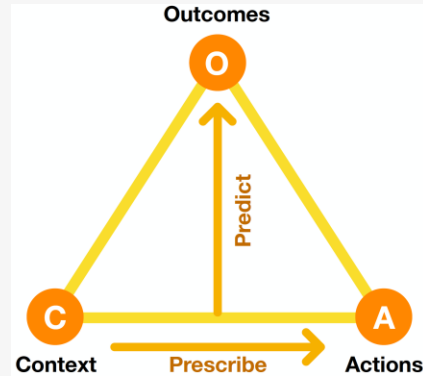
Making recommendations explainable: Evolve rulesets

```

<> (0.07*context_12 < 0.16*context_6) --> 0.92*C2_Workplace closing
<> (0.54*context_17 >= 0.03*context_16) (0.46*context_3 >= 0.48*context_11) --> 0.15*C6_Stay at home requirements
<> (0.93*context_16 > 0.46*context_19) (0.82*context_2 > 0.42*context_4) (0.54*context_17 >= 0.03*context_16) (0.47*context_9 <= 0.72*context_11) (0.46*context_3 >= 0.48*context_11) (0.46*context_17*2 >= 0.48*context_11)
(0.46*context_17 >= 0.48*context_11) (0.30*context_7 >= 0.29*context_4) (0.16*context_4*3 > 0.15*context_18) (0.16*context_4 > 0.15*context_18) (0.16*context_13 > 0.15*context_18) (0.10*context_6*2 <= 0.95*context_16) (0.10*context_6 <=
0.95*context_16) (0.10*context_6 <= 0.95*context_16) --> 0.15*C6_Stay at home requirements
<> (0.54*context_17 >= 0.03*context_16) (0.46*context_3 >= 0.48*context_11) (0.46*context_17 >= 0.48*context_11) (0.38*context_12 <= 0.22*context_1) (0.38*context_12 <= 0.22*context_1) (0.16*context_4 > 0.15*context_18)
(0.10*context_6*2 <= 0.95*context_16) (0.10*context_6 <= 0.95*context_16) (0.10*context_6 <= 0.95*context_16) (0.10*context_6 <= 0.95*context_16) --> 0.75*C6_Stay at home requirements
<> (0.18*context_18 <= 0.62*context_12) --> 0.95*C4_Restrictions on gatherings
<> (0.38*context_4 >= 0.26*context_16) (0.18*context_18 > 0.62*context_12) --> 0.95*C4_Restrictions on gatherings
<> (0.07*context_12*2 < 0.16*context_6) --> 0.92*C2_Workplace closing
<> (0.46*context_3 >= 0.48*context_11) (0.16*context_4 > 0.15*context_18) --> 0.71*C6_Stay at home requirements
<> (0.16*context_4 > 0.15*context_18) --> 0.71*C6_Stay at home requirements
<> (0.33*context_10 < 0.27*context_5) (0.00*context_2 < 0.24*context_16) --> 0.72*C5_Close public transport
<> (0.71*context_12 >= 0.57*context_7) (0.63*context_11 >= 0.60*context_8) (0.29*context_16 >= 0.26) (0.27*context_4 > 0.14*context_4) --> 0.72*C5_Close public transport
<> (0.75*context_13 > 1.00*context_1) (0.07*context_12 < 0.16*context_6) --> 0.92*C2_Workplace closing
<> (0.58*context_17 <= 0.89*context_19) (0.39*context_10 > 1.00*context_12) --> 0.82*C7_Restrictions on internal movement
<> (0.71*context_12 >= 0.57*context_7) (0.63*context_11 >= 0.60*context_8) (0.29*context_16 >= 0.26) (0.24*context_3 >= 0.63*context_3) --> 0.36*H3_Contact tracing
<> (0.71*context_12 >= 0.57*context_7) (0.63*context_11 >= 0.60*context_8) --> 0.36*H3_Contact tracing
<> (0.54*context_17 >= 0.03*context_16) (0.46*context_3 >= 0.48*context_11) (0.16*context_4 > 0.15*context_18) --> 0.71*C6_Stay at home requirements
<> (0.54*context_17 >= 0.03*context_16) (0.46*context_17 >= 0.48*context_11) (0.33*context_10 >= 0.36*context_13) (0.16*context_4 > 0.15*context_18) --> 0.71*C6_Stay at home requirements
<> (0.54*context_17 >= 0.03*context_16) (0.16*context_4 > 0.15*context_18) (0.10*context_6*2 <= 0.95*context_16) --> 0.71*C6_Stay at home requirements
<> (0.29*context_16 >= 0.26) --> 0.36*H3_Contact tracing
<> (0.07*context_12 < 0.16*context_6) --> 0.92*C2_Workplace closing
<> (0.54*context_17 >= 0.03*context_16) --> 0.71*C6_Stay at home requirements
<> (0.56*context_17 >= 0.49*context_18) (0.49*context_0 > 0.90*context_10) (0.01*context_16 >= 0.31*context_1) --> 0.42*C3_Cancel public events
<> (0.71*context_12 >= 0.57*context_7) (0.63*context_11 >= 0.60*context_8) (0.29*context_16 >= 0.26) --> 0.36*H3_Contact tracing
<> (0.45*context_4 < 0.13*context_0) (0.04*context_19 < 0.54) --> 0.95*H1_Public information campaigns
<> (0.71*context_16 >= 0.00) (0.07*context_12 < 0.16*context_6) --> 0.92*C2_Workplace closing
<> (0.21*context_4 <= 0.23*context_7) (0.07*context_12 < 0.16*context_6) (0.07*context_12 < 0.16*context_6) --> 0.92*C2_Workplace closing
<> (0.33*context_10 < 0.27*context_5) (0.03*context_17 > 0.82*context_14) --> 0.72*C5_Close public transport
<> (0.58*context_17 <= 0.89*context_19) --> 0.82*C7_Restrictions on internal movement
<> (0.58*context_9 > 0.74*context_2) (0.25*context_2 < 0.84*context_3) --> 0.34*H2_Testing only
<> (0.49*context_0 > 0.90*context_10) --> 0.42*C3_Cancel public events
<> (0.04*context_19 < 0.54) --> 0.95*H1_Public information campaigns
<> (0.33*context_10*2 < 0.27*context_5) (0.03*context_17 > 0.82*context_14) --> 0.72*C5_Close public transport
<> (0.54*context_17 >= 0.03*context_16) (0.46*context_3 >= 0.48*context_11) (0.46*context_3 < 0.48*context_11) (0.16*context_4 > 0.15*context_18) (0.10*context_6 < 0.95*context_16) --> 0.15*C6_Stay at home requirements
<> (0.54*context_17 >= 0.03*context_16) (0.46*context_3 < 0.48*context_11) (0.16*context_4 > 0.15*context_18) (0.10*context_6 < 0.95*context_16) --> 0.15*C6_Stay at home requirements
<> (0.54*context_17 >= 0.03*context_16) (0.46*context_3 >= 0.48*context_11) (0.46*context_3 < 0.48*context_11) (0.38*context_12 <= 0.22*context_1) (0.38*context_12 <= 0.22*context_1) (0.16*context_4 > 0.15*context_18) --> 0.75*C6_Stay at home requirements
<> (0.54*context_17 >= 0.03*context_16) (0.46*context_3 >= 0.48*context_11) (0.46*context_3 < 0.48*context_11) (0.38*context_12 <= 0.22*context_1) (0.38*context_12 <= 0.22*context_1) (0.16*context_4 > 0.15*context_18) --> 0.75*C6_Stay at home requirements
<> (0.54*context_17 >= 0.03*context_16) (0.46*context_3 >= 0.48*context_11) (0.46*context_3 < 0.48*context_11) (0.30*context_7 >= 0.29*context_4) (0.16*context_4 > 0.15*context_18) (0.10*context_6 < 0.95*context_16) --> 0.15*C6_Stay at home requirements
<> (0.54*context_17 >= 0.03*context_16) (0.46*context_3 >= 0.48*context_11) (0.46*context_3 < 0.48*context_11) (0.30*context_7 >= 0.29*context_4) (0.16*context_4 > 0.15*context_18) (0.10*context_6 < 0.95*context_16) --> 0.15*C6_Stay at home requirements
<> (0.18*context_18 > 0.62*context_12) --> 0.95*C4_Restrictions on gatherings
<> (0.46*context_3 >= 0.48*context_11) (0.10*context_6 <= 0.95*context_16) --> 0.00*C6_Stay at home requirements
<> (0.46*context_17 >= 0.48*context_11) (0.16*context_4 > 0.15*context_18) (0.10*context_6 <= 0.95*context_16) (0.10*context_6 <= 0.95*context_16) --> 0.15*C6_Stay at home requirements
<> Default Action: 0.12*C7_Restrictions on internal movement
  
```



Scaling up: XPRIZE Pandemic Response Challenge



November 2020-March 2021

- Phase 1: Prediction Accuracy; 100 teams narrowed down to 50 finalists
- Phase 2: Prescription Effectiveness; 2 winners (Valencia, Slovenia) and 8 runner-ups

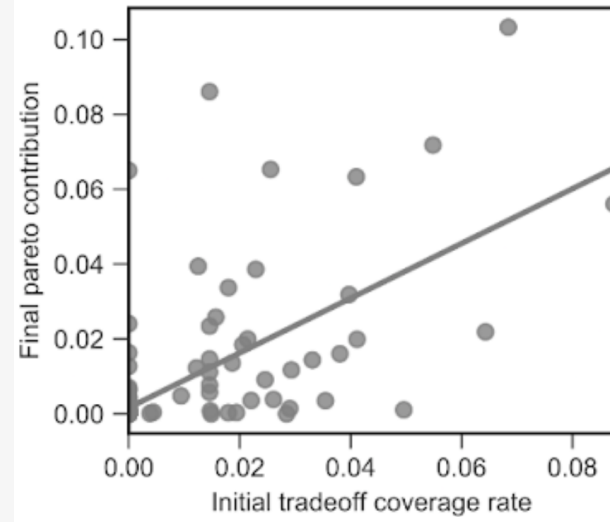
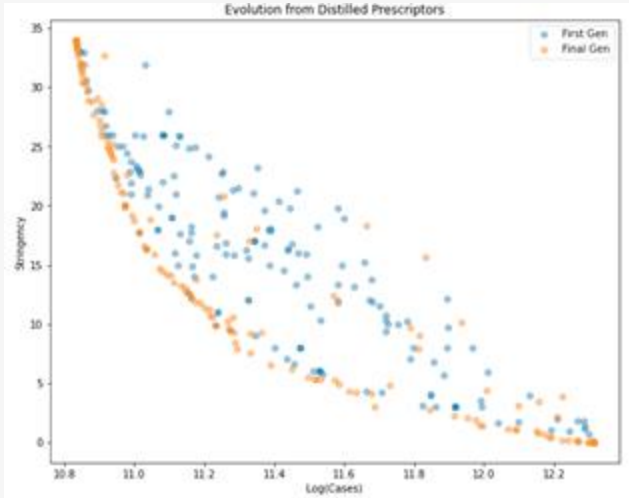
Many Machine Learning approaches as well as conventional ones

- Evaluation and analysis: <https://evolution.ml/xprize>

Informing government policy

- E.g. Team Valencia doing that already during the competition
- Embedded a government representative into the science team

Using AI to Leverage Human Insights



XPRIZE entries have many useful, diverse ideas
Evolutionary AI (RHEA) can be used to build on them

- Improve upon XPRIZE entries
- Improve upon evolution from scratch

Can realize latent potential hidden in poor entries
Technology to bring the community effort together

The Story Continues

Built the original demo to draw attention to science

- Decision makers, general public

XPRIZE amplified it tremendously

- Many people around the world could participate, publicize
- 1.2B views of the results

Follow-up: Pandemic Resilience (GPAI)

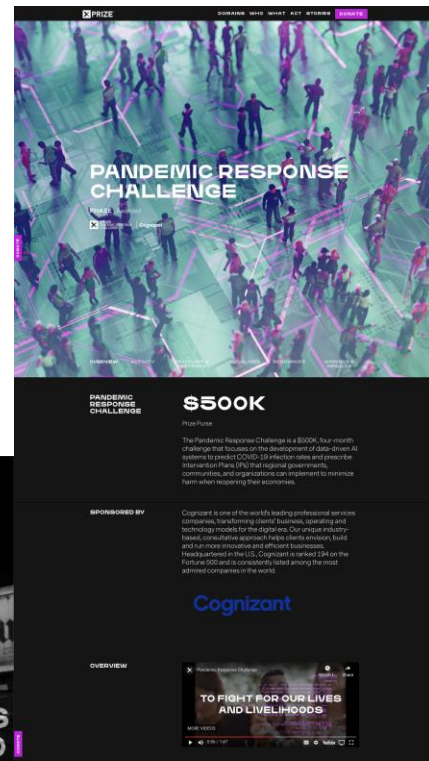
- Focusing on utilizing multiple models

Follow-up: PIPP (NSF)

- Focusing on science communication

Follow-up: Project Resilience (UN/ITU)

- Build an AI for Good ecosystem



Conclusions

Data-driven approach can be accurate, general, and adaptable

- Can make worthwhile discoveries

Making models useful for decision makers

- Alternatives (Pareto front)
- Interactive exploration (scratchpad)
- Uncertainty estimates (confidence bounds)
- Explainability (rule-sets)
- Combining human expertise and machine exploration (RHEA)

Future expansion

- Better predictive and prescriptive models
- Better communication with decision-makers and the public
- Expanding the scope to other fields

