**Slide 1**

Thanks – my name is Craig McGowan and my proposal centers on making accessible forecasts of influenza activity

**Slide 2**

I imagine most, if not all of us, have had at least one experience with the flu, probably one we’d be happy to never repeat. Maybe some of you have seen this diagnosis algorithm floating around on the internet – while this could work to determine if you *have* the flu, predicting flu activity is whole different question. Accurate predictions could help inform the public to seek out care, inform health care staffing and preparation, and more.

**Slide 3**

The Centers for Disease Control and Prevention publishes weekly flu levels for the nation, multi-state regions, and individual states, with the main measure of intensity being the % of doctor visits due to influenza-like illness. At the national level, illustrated in the top left plot, there were more visits for flu in early Feb compared to late Jan. But if we look at a regional pattern, shown in the middle, we can see spatial differences, and zooming in on Region 3 in the Mid-Atlantic shows even more differences between states. This all suggests that forecasting at these varying resolutions would have value for end users. For example, the federal government might care about national forecasts, while a pharmaceutical company producing vaccines or antivirals might care about regional or state forecasts to decide on product shipments or marketing.

**Slide 4**

To build my forecasts, I used CDC surveillance data on flu activity and flu virus types. I used % of doctor visits for flu as my measure of flu activity. These data are collected weekly and available back to 1997 for the US and regions, and back to 2010 for individual states. I also used Google Trends data, available weekly from 2004. Forecasts are based on a dynamic harmonic regression model, where I use Fourier decompositions for the seasonality, ARIMA errors for remaining autocorrelation, and covariates including Google Trends and flu virus types. Forecasts from this model are combined in a weighted ensemble with the results of two naïve baseline models to create the final forecasts. To train the models, I fit weekly forecasts for each CV season to determine the best model structure for each location, which ended up being ~ 14K CV forecasts. From the final forecasts, I estimated the ensemble weights using leave one season out cross validation.

**Slide 5**

Looking at prospective forecasts for 2018/2019 season, the forecasts have performed quite well. I’ve highlighted the performance for the US, the previously highlighted Region 3, and two states within that as examples. As expected, MAE increases with time horizon, but up to 2 weeks ahead mean error is still within a little over 0.5% for all locations. We see the value of forecasts at different spatial scales as well – the US, Reg 3, and VA are all forecast to decline, while if any of you live in PA you might want to keep washing your hands as levels are predicted to stay steady.

**Slide 6**

At The Data Incubator, I plan to expand this by finishing forecasts for the remaining states and creating an interactive visualization for users to explore forecasts at different scales. Rather than the static mockups displayed here, users could click on regions within the map and bring up forecasts for those regions, providing valuable insights to individuals, health care providers, and public health officials.

Nation getting smaller