**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. And while there exists at least one simple heuristic algorithm for determining 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**

Key question for forecasts is what area to forecast for? 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. If we look at the change in % visits for ILI from late Jan to early Feb nationally, shown in the top left plot, flu activity is going up. But if we look at a regional pattern, shown in the middle, or state pattern, in the bottom right, we see spatial differences suggesting that forecasting at those resolutions would have value for end users. For example, the national 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 ILI activity and flu virus types. I used % visits for ILI 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. The model is 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 on the CV seasons.

**Slide 5**

Looking at prospective forecasts for 2018/2019 season, the forecasts have performed quite well. I’ve highlighted the performance for the US, Region 3, and two states within Region 3 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 levels in PA are forecast to stay fairly 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 images displayed here, users could click on regions within the map and bring up forecasts for those regions, as well as measures of accuracy. By providing a sense of