Humanitas

A prediction tool for volatile commodity prices in developing countries

Students: Alexander John Busser, Anton Ovchinnikov, Ching-Chia Wang, Duy Nguyen, Fabian Brix, Gabriel Grill, Julien Graisse, Joseph Boyd, Stefan Mihaila

Time Series data

Different sources Price categories: Retail prices, wholesale prices

Wholesale prices

Wholesale price index

(taken from investopedia.com)
An index that measures and tracks the changes in price of goods in the stages before the retail level. Wholesale price indexes (WPIs) report monthly to show the average price changes of goods sold in bulk, and they are a group of the indicators that follow growth in the economy.

Although some countries still use the WPIs as a measure of inflation, many countries, including the United States, use the producer price index (PPI) instead.

Price sequences

Preprocessing

load data from csv into pandas dataframe
removing NAs

Other sources

distribution & production
exchange rate crude oil

Social Media data

Twitter

Historical tweets

Approach 1: Fetching "historical" tweets through Twitter API

Using the Twython package for python we are able to interface with the Twitter API. Our methodology (figure 0.1) is to select the twitter accounts of a number of

regional celebrities as starting points. These are likely to 'followed' by large numbers of local users. In a first phase (TWEET_COLLECTION.py.get_followers()), from each of these sources we may extract a list of followers and filter by various characteristics. Once a substantial list has been constructed it must be merged (merge.py and remove_intersection.py), we may proceed to download the tweet activity (up to the 3200 most recent tweets) of each of these users in a second phase (TWEET_COLLECTION.py.get_tweets()).

Despite recent updates allowing developers greater access, Twitter still imposes troublesome constraints on the number of requests per unit time window (15 minutes) and, consequently, the data collection rate. It is therefore necessary to: 1) optimise the use of each request; and 2) parallelise the data collection effort.

As far as optimisation is concerned, the **GET statuses/user_timeline** call may be called 300 times per 15 minute time window with up to 200 tweets returned per request. This sets a hard upper bound of 60000 tweets per time window. This is why the filtering stage of the first phase is so crucial. Using the **GET followers/list** call (30 calls/time window), we may discard in advance the majority of twitter users with low numbers of tweets (often zero), so as to avoid burning the limited user timeline requests on fruitless users, thus increasing the data collection rate. With this approach we may approach optimality and achieve 4-5 million tweets daily per process. However, it may be prudent to strike a balance between tweets per day and tweets per user. Therefore a nominal filter is currently set to 50 tweets minimum rather than 200. It is furthermore necessary to install dynamic time-tracking mechanisms within the source code so as to monitor the request rates and to impose a process 'sleep' when required.

Parallelisation begins with obtaining N ($\approx$ 10) sets of developer credentials from Twitter (https://dev.twitter.com/). These N credentials may then be used to launch N processes (get_users.sh) collecting user data in parallel. Given the decision to divide the follower collection and tweet collection into separate phases (this may alternatively be done simultaneously), there is no need for distributed interaction between the processes to control overlap, as each process will simply take $1/N$ th of the follower list produced in phase 1 and process it accordingly. It should be relatively simple to initiate this parallel computation given the design of the scripts.

A benchmarking test (table 0.1) performed in order to support configuration choices for the parallelisation. The test involved collecting the tweets from all good users within the first 20000 followers of @KareenaOnline, the account of a local celebrity. The following observations can be made:

- only 1.5-2% of users are considered "good" under the current choice of filters (location, min. 50 tweets etc.);

Phase 1				
Users	Duration (s)	Sleep (s)	User Rate	Type
334	2795	2047	-	Total
299	2700	2047	99.7	Normalised (3 windows)
Phase 2				
Tweets (Users)	Duration (s)	Sleep (s)	Tweet Rate	Type
171990 (334)	3108	922	-	Total
150008 (309)	2700	922	50002.7	Normalised (3 windows)

Table 0.1: A picture of the same gull looking the other way!

- Despite different levels of sleeping, phase 2 reads from users at roughly the same rate that phase 1 collects them (approximately 100 per time window in both cases);

- Phase 2 produces around 50000 tweets per time window.

It is important to note however, that the rate of "good" users increases varies depending on the notoriety of the source account outside of India. To ensure good coverage for user collection, a wide variety of source users was chosen including rival politicians, musicians, sportspersons, film stars, journalists and entrepreneurs.

Tweet collection for Humanitas occurred in two main waves. In the first wave 180 000 users identifiers were collected. This amounted to 110 million tweets, collected over about three days, totalling 288GB of information (note a tweet response comprises the textual content as well as a substantial amount of meta data). In second wave of collection we encountered the effect of diminishing returns as many of the newly harvested users had already featured in the first wave. Despite a lengthier collection effort, only 110 000 new users were collected, leading to 70 million additional tweets and a grand total for the two waves of about 500GB of data. Future collection work for Humanitas would benefit from a more sophisticated approach, for example, by constructing a Twitter user graph.

Approach 2: Filtering tweets provided by webarchive.org

https://archive.org/details/twitterstream

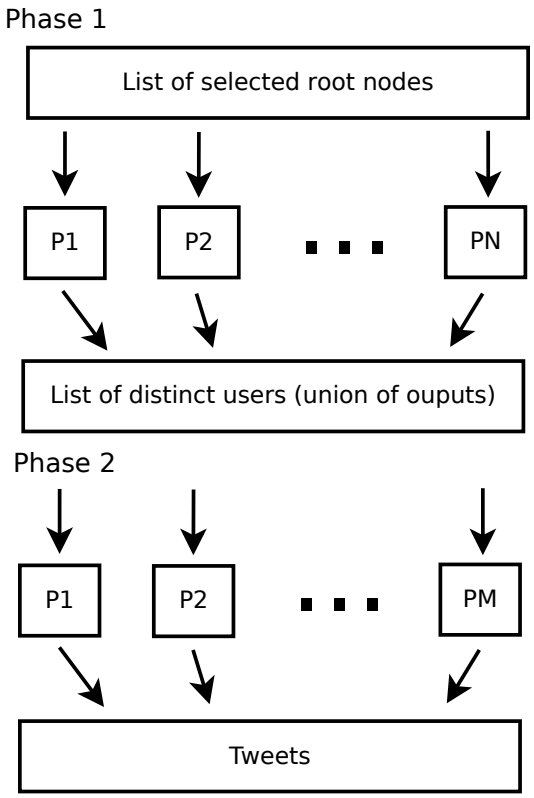


Figure 0.1: Tweet collection methodology.

Daily? tweet aggregator

Clustering according to keywords

Issue of localization

Geolocalized tweets

Filtering the available archives of tweets taken from the API yielded near to no geolocalized tweets from India matching our set of keywords. This reason is evident, because the twitter API only allows extraction of 1% of tweets and only 2% of tweets are actually geolocalized. In effect, getting tweets that match our keywords specific to food commodities is very unlikely. We had more luck with tweets from Indonesia, however as already explained we were unable to attain enough price sequences from Indonesia to actually train a model. Furthermore, the time constraints didn't allow us to get tweets from India and Indonesia in parallel in order to do some "stand-alone" clustering analysis.

Approximation: Mapping tweets to user location

Processing

Merging Series

Crafting indicators from tweets

Price Transmission Analysis

Interpretation

automate interpretation to a certain extent by learning about circumstances through online data.

Time Series Analysis

Time series data has a natural temporal relation between different data points. It is important in the analysis to extract significant temporal statistics out of data. We will focus on analyze stationarity, autocorrelation, trend, volatility change, and seasonality of our price datasets in R.

Stationarity of a series guarantees that the mean and variance of the data do not change over time. This is crucial for a meaningful analysis, since if the data is not stationary, we can not be sure that anything we derive from the present will

be consistent in the future. We can transform our data into a stationary one by taking k-th difference to remove the underlying trend, and then apply standard test procedures such as KPSS test [1] to see if the differenced series is stationary.

Autocorrelation is another important trait in time series data. It suggests the degree of correlation between different time periods. By plotting correlograms (autocorrelation plots) of our data, we will be able to identify if the fluctuation of prices may be due to white noise or other hidden structures.

Seasonality is reasonably expected in our agricultural related time series. Several methods might help us to detect seasonality, such as common run charts, seasonal subseries plots, periodograms, and the correeologrames we mentioned before.

(trend and volatility change is straightforward and can be concluded once we have the datasets)

[1] Kwiatkowski, D.; Phillips, P. C. B.; Schmidt, P.; Shin, Y. (1992). "Testing the null hypothesis of stationarity against the alternative of a unit root". Journal of Econometrics 54 (1âĂŞ3): 159âĂŞ178.

Prediction Models

Time Series Forecasting

ARMA Model

The classical Time series forecasting approach is to use the ARMA (Auto-Regressive Moving Average) model to predict the target variable as a linear function which consists of the auto-regressive part (lag variables) and the moving average part (effects from recent random shocks).

The ARMA(p,q) model: (will refine math representations later)

$Phi(B) * Y_t = Theta(B) * eps_t$

The fitting of the model and the historical data can be accomplished by maximum likelihood estimation.

Regression

We can also apply ARMA to the linear regression model. It is formulated as such:

$Y = Beta * X + eps, eps\ ARMA(p, q)$

Through OLS (Ordinary Leasat Square) or GLS (General Least Square) processes, we can obtain an optimal Beta.

Multilayer Perceptrons

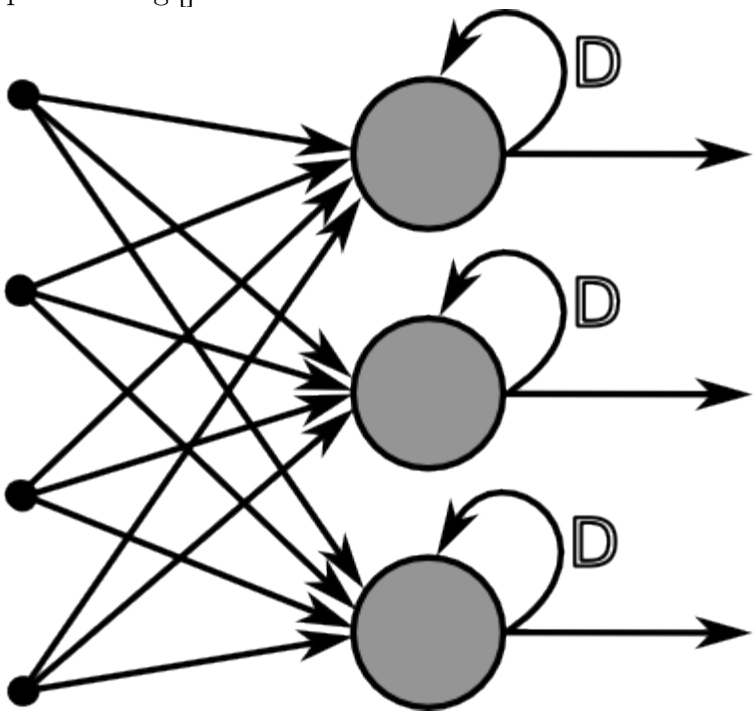
taken from M. Seegers course on Pattern Recognition and ML

Recurrent Neural Networks (RNN)

source: scholarpedia A recurrent neural network (RNN) is a neural network in with feedback connections, enabling signals to be fed back from a layer l in the network to a previous layer.

Simple Recurrent Networks

The simplest form of an RNN consists of an input, an output and one hidden layer as depicted in fig.[].



[source: wikipedia]

General description of a discrete time RNN

A discrete time RNN is a graph with K input units $\mathbf{u}$, N internal network units $\mathbf{x}$ and L output units $\mathbf{y}$. The activation (per layer) vectors at point n in time are denoted by $\mathbf{u}(n) = (u_1(n), ..., u_n(n))$, $\mathbf{x}(n) = (x_1(n), ..., x_n(n))$, $\mathbf{y}(n) = (y_1(n), ..., y_n(n))$. Edges between the units in these sets are represented by weights $\omega_{ij} \neq 0$ which are gathered in adjacency matrices. There are four types of matrices:

- $\mathbf{W}^{in}_{N\times K}$ contains inputs weigths for an internal unit in each row respectively

- $\mathbf{W}_{N\times N}$ contains the internal weights. This matrix is usually sparse with densities $5\% - 20\%$
- $\mathbf{W}^{out}_{L\times(K+N+L)}$ contains the weights for edges, which can stem from the input, the internal units and the outputs themselves, leading to the output units.
- $\mathbf{W}^{back}_{N\times L}$ contain weights for the edges that project back from the output units to the N internal units

In a *fully recurrent network* every unit receives input from all other units neurons and therefore input units can have direct impact on output units. Output units can further be interconnected.

Evaluation The calculation of the new state of the internal neurons in time-step $n+1$ is called evalution.

$$\mathbf{x}(n+1) = \mathbf{f}(\mathbf{W}^{in}\mathbf{u}(n+1) + \mathbf{W}\mathbf{x}(n) + \mathbf{W}^{back}\mathbf{y}(n))$$

where $f = (f_1, ..., f_N)$

Exploitation The output activations are then computed from the internal state of the network in the exploitation step.

$$\mathbf{y}(n+1) = f^{out}(\mathbf{W}^{out}(\mathbf{u}(n+1), \mathbf{x}(n+1), \mathbf{y}(n)))$$

where $f^{out} = (f^{out}_1, ..., f^{out}_L)$ are the output activation functions and the matrix of output weights is multiplied by the concatenation of input, internal and previous output activation vectors.

RNNs can in theory approximate any dynamical system with chosen precision, however training them is very difficult in practice.

Echo State Networks

Echo State Networks (ESN) are a type of discrete time RNNs for which training is straightforward with linear regression methods. The temporal inputs to the network are transformed to a high-dimensional *echo state*, described by the neurons of a sparsely connected *random* hidden layer which is also called a reservoir. The output weights are the only weights in the network that can change and are trained in a way to match the desired output. ESNs and the related liquid state machines (LSMs) form the field of *reservoir computing*.

Echo State Property

The intuitive meaning of the *echo state property* (ESP) is that the internal state is **uniquely** determined by the history of the input signal and the teacher forced output, given that the network has been running long enough. Teacher forcing essentially means that the output $\mathbf{y}(n-1)$ is forced to be equal to the next time series value $\mathbf{u}(n)$ and thus to the next input.

Definition 1 *For every left infinite sequence* $(\mathbf{u}(n), \mathbf{y}(n-1)), n = \ldots, -2, -1, 0$ *and all state sequences* $\mathbf{x}(n), \mathbf{x}'(n)$ *which are generated according to*

$$\mathbf{x}(n+1) = \mathbf{f}(\mathbf{W}^{in}\mathbf{u}(n+1) + \mathbf{W}\mathbf{x}(n) + \mathbf{W}^{back}\mathbf{y}(n))$$
$$\mathbf{x}'(n+1) = \mathbf{f}(\mathbf{W}^{in}\mathbf{u}(n+1) + \mathbf{W}\mathbf{x}'(n) + \mathbf{W}^{back}\mathbf{y}(n))$$

it holds true that $\mathbf{x}(n) = \mathbf{x}'(n)$ *for all* $n \leq 0$.

The echo state propery is ensured through the matrix of internal weights W

Theorem 1 *Define* σ_{max} *as largest singular value of* $\mathbf{W}$, λ_{max} *as largest absolute eigenvalue of* $\mathbf{W}$.

1. *If* $\sigma_{max} < 1$ *then the ESP holds for the network*
2. *If* $\|\lambda_{max}\| > 1$ *then the network has no echo states for any input/output interval which contains the zero input/output tuple (0,0)*

In practice is suffices to make sure the negation of the second point holds.

Training the ESN

"The state of the ESN is therefore a function of the finite history of the inputs presented to the network. Now, in order to predict the output from the states of the oscillators the only thing that has to be learned is how to couple the outputs to the oscillators, i.e. the hidden to output connections:" http://stackoverflow.com/questions/21940860/e state-network-learning-mackey-glass-function-but-how

Hyperparameters: dimensionality of W, spectral radius α

Initial state determination The network is run for a first set of inputs and the results are then discarded. If the spectral radius is close to unity, implying slow forgetting of the starting state, the initial set has to be a substantial part of the training dataset.

"Likewise, when the trained network is used to predict a sequence, a long initial run of the sequence must be fed into the network before the actual prediction can start. This is a nuisance because such long initial transients are in principle unneccessary"

"By contrast, a recurrent neural network such as our echo state network, but also such as the networks used in [5] need long initial runs to âĂIJtune inâĂİ to the to-be-predicted sequence. [5] tackle this problem by training a second, auxiliary âĂIJinitiatorâĂİ network." EchoStatesTechRep.pdf, p.32

Teacher forcing

Feedback

Batch learning

Ridge Regression

Leaky integrator neurons *Taken from Echo State Tech Rep. page 26/27*
In order for the Echo State Network to be able to learn slowly and continuously changing dynamics and thereby to capture longterm phenoma in the price sequences we feed in, we need a way to introduce continuous dynamics. This is done via approximation of the differential equation of a continuous-time leaky integrator network

$$\frac{d\mathbf{x}}{d\mathbf{t}} = C(-\alpha\mathbf{x} + \mathbf{f}(\mathbf{W}^{in}\mathbf{u}(n+1) + \mathbf{W}\mathbf{x}(n) + \mathbf{W}^{back}\mathbf{y}(n))) \tag{1}$$

where C is a time constant and α the leaking decay rate. For the approximation we introduce a stepsize δ:

$$\mathbf{x}(n+1) = (1 - \delta C\alpha) + \delta C(\mathbf{f}(\mathbf{W}^{in}\mathbf{u}(n+1) + \mathbf{W}\mathbf{x}(n) + \mathbf{W}^{back}\mathbf{y}(n)))$$

Theorem 2 *Let a network be updated according to*

Online learning with Recursive Least Squares (RLS) update weights in each iteration ...

Parameter selection with Maximum Entropy Bootstrap (Meboot) In order to find the best parameters for generalization during training of the neural network models with we create replicate time series of a selected price sequence dataset. The method we employ to this end is called 'Maximum Entropy Bootstrap' (meboot) and was introduced by H.D. Vinod in 2006. [reference]. The reason for the use of this specific method is that, due to temporal dependence, time series cannot simply be randomly sampled into a new dataset. The meboot algorithm allows for construction of random replicates of the given time series showing the same statistical properties.

RNN with backpropagation decorrelation algorithm