What about Time Series? Applying polyreg and toweranNA to Time Series

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Bay Area R Users Group
GRAIL, June 11, 2019

(slides will be available at
http://heather.cs.ucdavis.edu/TimeSeries.pdf)

Introduction

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Current talk:

- Apply these methods to time series.

What about Time Series?

- How adapt **polyreg**, **toweranNA** to time series?

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What about Time Series?

- How adapt **polyreg**, **toweranNA** to time series?
- Say predict X_i from $X_{i-1}, X_{i-2}, ..., X_{i-m}$, lag m.
- E.g. lag 3:

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- Say predict X_i from $X_{i-1}, X_{i-2}, ..., X_{i-m}$, lag m.
- E.g. lag 3:

  x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12},... now stored as data matrix

x_1	x_2	x_3	x_4
x_2	x_3	x_4	x_5
x_3	x_4	x_5	x_6
...	...	...	...

Columns 1-3 are "X", col. 4 is "Y". Run model (poly, NN, whatever) to predict Y col. from X cols.

Covariates

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Covariates

E.g. what if have a single covariate C, with its own time series?

x_1	x_2	x_3	c_1	c_2	c_3	x_4
x_2	x_3	x_4	c_2	c_3	c_4	x_5
...	...	...	...	...	...	...

Now cols. 1-6 are "X", col. 7 is "Y."

Does It Work?

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Does It Work?

- Work in progress.
- Early results very promising.

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polyreg and NNs

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Summary of earlier talk:

- Neural nets (NNs) essentially = polynomial regression (PR).
- NOT a "universal approximation theorem"; refers to actual internal operation of NNs.
- Thus, PR should (and does) give results as good as, or better than, NNs.
- Why "or better than"?

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- Neural nets (NNs) essentially = polynomial regression (PR).
- NOT a "universal approximation theorem"; refers to actual internal operation of NNs.
- Thus, PR should (and does) give results as good as, or better than, NNs.
- Why "or better than"? NNs may converge to local min, wrong answer.

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- Motivated by NN=PR: use PR instead of NNs.
- Generates all possible d-degree polynomials in p variables. (**Not so easy.** E.g. must skip powers of dummy variables.)
- Has dimension reduction options.
- On CRAN, but latest at *github.com/matloff/polyreg*.

Key polyreg functions

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```
polyFit(function (xy, deg, maxInteractDeg = deg,
    use = "lm", pcaMethod = NULL, pcaLocation =
    "front", pcaPortion = 0.9, glmMethod = "one",
    return_xy = FALSE, returnPoly = FALSE)

predict.polyFit(object, newdata, ...)
```

E.g. if choose dimension reduction by PCA in **polyFit()**, **predict()** will automatically take care of it.
Various other dim. reduction, helper functions.

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- Etc.
- Polynomial regression!
- **Important note:** The degree of the fitted polynomial in NN grows with each layer.

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- What about reLU? Same analysis, but now have piecewise polynomials, so NN=PPR.
- Even without Taylor series etc.] any reasonable activation function is "close" to a polynomial.
- Hence NN=PR.

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Possible drawbacks/remedies of PR:

- Large memory requirement. Maybe use R's **bigmemory** package (with backing store).
- Run time (worse than NN?). Remedy with C code, and/or GPU.

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- Compared PR vs. NNs on a wide variety of datasets.
- In every single dataset, **PR matched or exceeded the accuracy of NNs**.
- Note:
  - Some attempt at optim, but certainly not exhaustive.
  - **Warning:** Beware of "p-hacking" effects. Don't take timings rankings overly seriously.

Times Series Example I

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- *https://github.com/jbrownlee/Datasets*

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setting	RMSE
JB NN, lag 1	58.88
PR lag 1, deg 2	33.99
PR lag 5, deg 3	26.86

Time Series Example II

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- Electric power demand.

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setting	accuracy
DCNN, lag 1	0.88
PR lag 10, deg 3	0.88
Keras, ts matrix	“Broken Clock”

Missing Values

- A perennial headache.
- Vast, VAST literature.
- Major R packages, e.g. **mice** and **Amelia**.
- New CRAN Task View, already quite extensive.

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- Non-imputational.
- Available at `http://github.com/matloff/toweranNA`.

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Theorem from Probability Theory

[Please be patient; R code and real-data examples soon. :-)]

Famous formula in probability theory:

$$EY = E[E(Y|X)] = E[g(X)]$$

Here $g()$ is regression function of Y on X.

Theoretical Background for Use in MVs

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- (Matloff, *Biometrika*, 1981)

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- My context: Est. E(Y).

$$\widehat{EY} = \frac{1}{n} \sum_{i=1}^{n} \widehat{g}(X_i)$$

Here $\widehat{g}$ comes from linear model, logit, nonpar.

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- But all theoretical. Not used (or even known) by MV practitioners.

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Why is this relevant to us?

- Y: variable to be predicted
- U: vector of known predictor values
- V: vector of uknown predictor values

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- But then must estimate many E(Y | U), since many different patterns for MVs (2^5 here).

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- Hard enough to fit one good model, let alone dozens or more.
- With Tower, need only one.

Tower (cont'd.)

Basic idea:

- Fit full regression model to the complete cases.
- Use Tower to get the marginal models from the full one:

$$\widehat{E}(Y \mid U = s) = \text{avg. } \underbrace{\widehat{E}(Y \mid U = s, V)}_{\text{full model}}$$

  over all complete cases with $U = s$

- In practice, use $U \approx s$ instead of $U = s$, using k nearest neighbors.

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- In practice, use $U \approx s$ instead of $U = s$, using k nearest neighbors.

  In practice, $k = 1$ usually fine; fitted values already smoothed, don't need more smoothing.

Census Example (cont'd.)

(a) Use, say, **lm()** on the complete cases, predicting wage income from (age,gender,education,occupation,weeks worked).

(b) Save the fitted values, e.g. **fitted.values** from **lm()** output.

(c) Say need to predict case with education = MS, occupation = 102, weeks worked = 52 but with age and gender missing.

(d) Find the complete cases for which (education,occupation,weeks worked) = (MS,102,52).

(e) Predicted value for this case is average of the fitted values for the cases in (d).

toweranNA Package API

- **toweranNA(x,fittedReg,k,newx,scaleX=TRUE)**
  - **x:** Data frame of complete cases.
  - **fittedReg:** Estimated values of full regress. ftn. at those cases (from **lm()**, **glm()**, random forests, neural nets, whatever).
  - **k:** Number of nearest neighbors.
  - **newx:** Data frame of new cases to be predicted.
  - Return value: Vector of predictions.

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Other Major Functions

Other Major Functions

- **towerLM(x,y,k,newx,useGLM=FALSE)**
  Wrapper for **toweranNA()**.
- **towerTS(x,lag,k)**
  Adaptation of Tower Method for time series; see below.

Structure of Examples

- 3 real datasets.
- Break into random training and test sets.
- Predict all test-set cases with at least one MV.

Example: WordBank Data

- Kids' vocabulary growth trajectories.
- About 5500 cases, 6 variables. About 29% MVs.

Mean Absolute Prediction Errors:

Amelia	Tower
102.7	96.2
122.9	119.9
89.4	88.1
115.3	107.0
111.1	102.5

- Times about 6s each.
- The **mice** package crashed.

UCI Bank Data

- About 50K cases.
- Only about 2% MVs. Not much need for MV methods, but let's make sure Tower doesn't bring harm. :-)
- Tower run 8.3s, **mice** 442.2s.
- Too long to do multiple runs. About the same accuracy, 0.92 or 0.93.
- **Amelia** crashed.

World Values Study

- World political survey.
- 48 countries, sample 500-3500 from each.
- MVs artifically added.
- Tower outperformed **mice** in 39 of 48 countries.

	Tower	*Mice*
Mean Absolute Predictive Error	1.7603	1.8270
Elapsed Time (seconds)	0.1825	14.0822

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- Most MV methods assume MAR, Missing at Random.
- Precise def. of MAR tricky (Seaman, *Stat. Sci.*, 2013).
- Tower assumptions similar, but assumptions matter much less in prediction than in estimation.
- **Amelia**, **mice** assume X multvar. normal, very distorting.

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Time Series (cont'd.)

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- A work in progress.

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Time Series (cont'd.)

- A work in progress.
- Example: NH4 data in imputeTS package.

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Time Series (cont'd.)

- A work in progress.
- Example: NH4 data in imputeTS package.
- Mean Absolute Prediction Error:
  na.ma (based on moving avg.): 1.51
  towerTS: 1.37

Future Work

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- E.g. have $p = 5$ predictors. Maybe fit four 4-predictor models. Each would be based on more complete cases than the 5-predictor models.

The Team!

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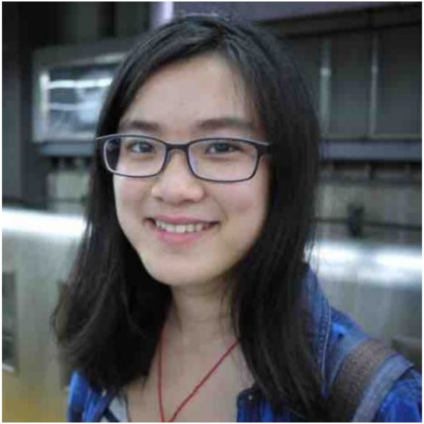
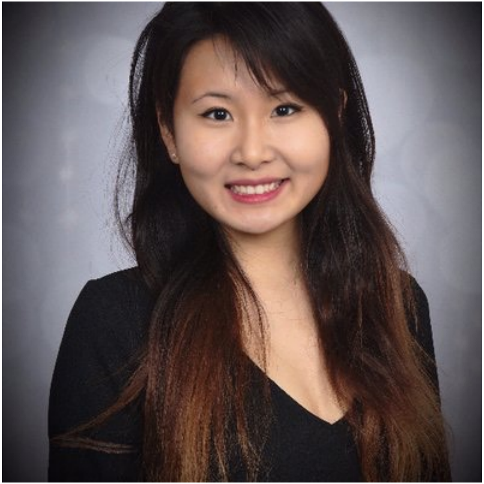


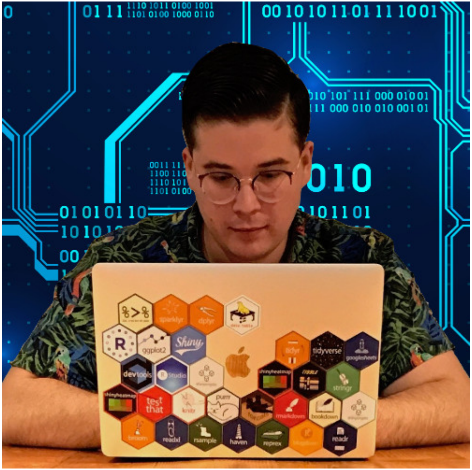
Xi Cheng

The Team! (contd.)



Tiffany Jiang

The Team! (contd.)



Bohdan Khomtchouk

The Team! (contd.)

Matt Kotila

The Team! (contd.)

Pete Mohanty

The Team! (contd.)

Robert Tucker

The Team! (contd.)

Robin Yancey

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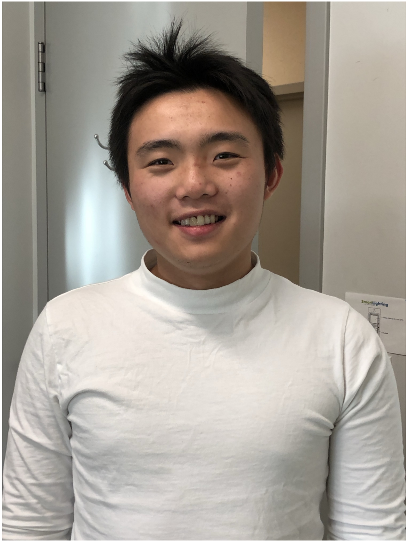

Allan Zhao