

# APPLYING LSTM TO TEXT GENERATION

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#### INTRODUCTION

- A conditional independence graph is a concise representation of pairwise conditional independence among many variables.
- We present a general framework for estimating pairwise conditional independence relationships among variables.

#### STABILITY SELECTION ALGORITHM

- Number of edges is a tuning parameter in any graphical model estimator.
- No obvious number constitutes a good choice.
- Stability Selection helps choosing the parameter  $(\lambda)$  with respect to a bound on the expected number of false positives  $\mu$ :

$$\lambda = \lfloor \sqrt{(2\omega - 1) \cdot \mu \cdot p \cdot (p - 1)/2} \rfloor$$

where  $\omega$  is a threshold of the minimum relative frequency of edges and p is the number of variables.

#### Pseudo code

Hyperparameters' initialization:  $\omega$ ,  $\mu$ 

Edges upper bound calculation  $(\lambda)$  given  $\omega$  and  $\mu$ 

k bootstraps resampling

Graph structure estimation with the learning procedure and  $\lambda$ 

Calculation of the edges frequency over the k graph

Estimation of the final graph structure in respect to the minimal frequency  $\omega$ 

### ALGORITHMS

# **Graphical Random Forest (GRaFo)**

Edges ranking scheme based on Random Forests' permutation importance measure.

#### Importance measure :

Predictor's relevance based on error difference between a regular Random Forest fit and a Random Forest fit within which one predictor's values are permuted.

#### Main steps:

- 1. Perform RF regression of a single variable on the remaining p-1 variables.
- 2. Calculate predictors' importance measure.
- 3. Repeat steps 1 and 2 for every p variables.
- 4. Define the (i, j) pair as i the outcome and j the predictor.
- 5. Best  $\lambda$  ranking pairs are added as edges.

## Graphical Lasso (GLasso)

Estimation of the regularized precision matrix  $\Lambda$  under multivariate normal hypothesis:

$$\hat{\mathbf{\Lambda}}_{GL} = \operatorname{argmax}_{\mathbf{\Lambda}} \left\{ \log |\mathbf{\Lambda}| - \operatorname{tr}(S\mathbf{\Lambda}) - \rho ||\mathbf{\Lambda}||_{1}^{1} \right\}$$

where S is the empirical covariance matrix and  $\rho$  the regularization term.

## Important points:

- The  $L_1$  regularization impose the sparsity of the precision matrix.
- Null covariance is equivalent to independence under normal distribution.
- Graphical Lasso is a good solution for estimate sparse undirected graphical models.

## REFERENCES

Meinshausen, N., Bhlmann, P., 2010. Stability selection. J Roy Stat Soc B 72, 417–473.

#### RESULTS

## Evaluation of known graph structures

• Analysis of the ROC curve (Sensitivity ~ Specificity):

Sensitivity = 
$$\frac{TP}{TP+FN}$$
 Specificity =  $\frac{TN}{TN+FP}$ 

• Selection criterion: graph structure maximizing sensitivity and specificity sum (symbolized by a black diamond on the graphics).

#### Scenario 1: Ising Model

• Simulate pairwise dependencies between a set of binary variables.

#### Scenario 2: Gaussian Networks

• Simulate continuous variables following multivariate Gaussian distribution with sparse covariance matrix.

#### Conclusion

- Stability selection algorithm stabilizes the graphical model estimation on artificial datasets.
- Graphical Lasso outperforms GRaFo algorithm.

#### BLABLABL

- Comorbidity: Any distinct additional clinical call entity that has existed during the clinical course of a patient.
- comorbidity factors.
- **Objective**: Profile the burden of comorbidity based on conditional dependences.
- CLSA database : 50,000 patients and 58 Conclusion
- Highlight mechanisms of disease purely based on observational data.
- Focus on few interesting associations which can then be specically tested in model organisms and clinical trials.