



JOHNS HOPKINS

WHITING SCHOOL
of ENGINEERING

Assessing Ventilator-Associated Pneumonia (VAP) in the PICU

Members:

Suraj Shah

Mentors:

Dr. Mathias Unberath

Clinical Collaborators:

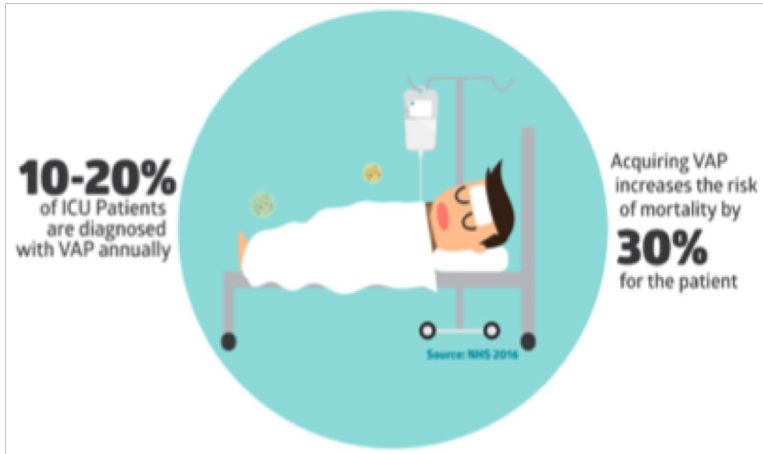
Dr. Jim Fackler

Dr. Jules Bergmann

Dr. Ferdinand Hui



Project Background



Chest X-Rays – empirical standard in diagnosing pneumonia

- 1 million diagnoses / year
- 50,000 deaths / year

Mechanical Ventilation – critical life sustaining ICU therapy

Risks of decompensation:

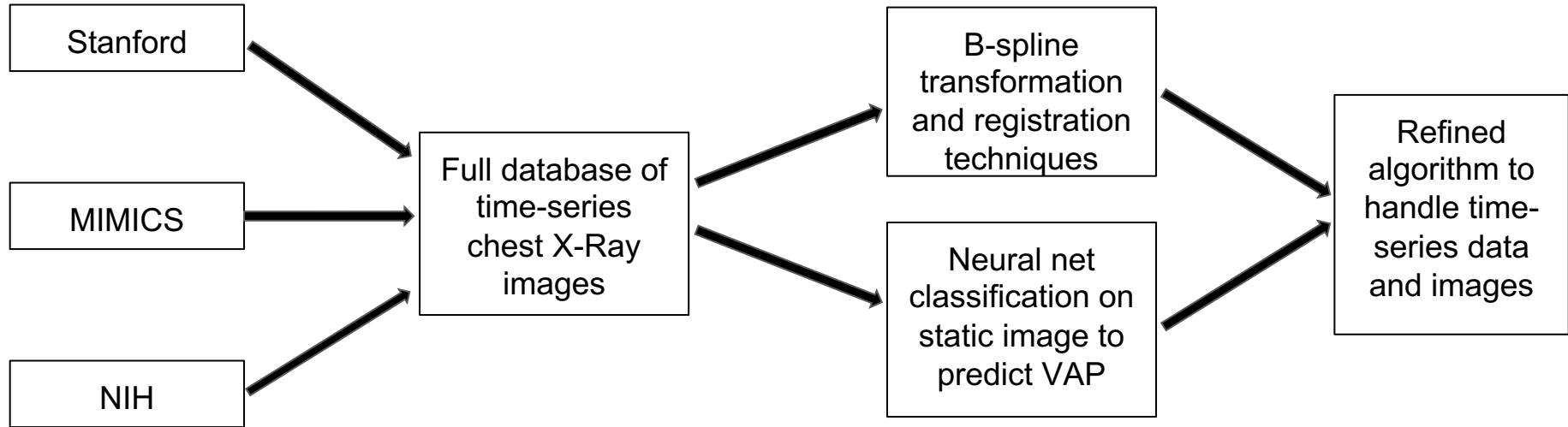
- Disease progression
- Latrogenic infection
- Ventilator injury

Objective: prepare automatic classifier to be used in the PICU to monitor VAP



Project Overview - Block Diagram

Public Datasets

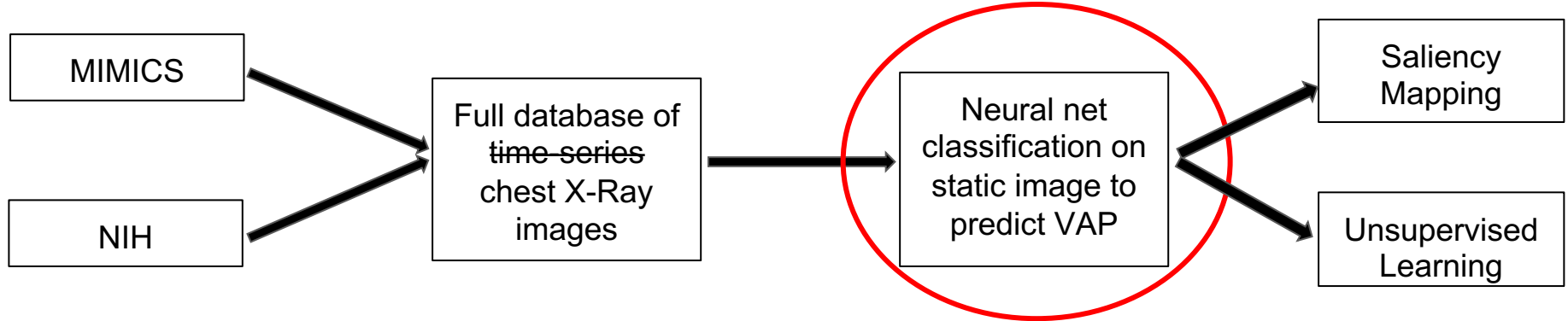


IRB Submission and Pending Approval for Pediatric Data from JHMI



Updated Project Overview - Block Diagram

Public Datasets



IRB Submission and Testing Data from JHMI



Deliverables

OLD

Minimum:

- A segmented database of X-ray cohorts
- Trained algorithm (pytorch model) for static image prediction

Expected

- ~~Algorithm for working image alignment with subsequent classification~~

Maximum

- ~~Sophisticated algorithm that handles arbitrary time series data for accurate prediction and monitoring~~

NEW

Minimum:

- A segmented database of X-ray cohorts
- Trained algorithm (pytorch model) for static image prediction

Expected

- Trained algorithm (pytorch model) for 3-class classification
- Trained saliency mapping algorithm for physician use

Maximum

- A trained pytorch model file for unsupervised learning of visual features
- Clinically actionable report of F1 scoring compared against current radiologists



Issues & Resolutions

Issues	Resolutions
<ul style="list-style-type: none">• Partner withdrew from class	<ul style="list-style-type: none">• Adjusted deliverables and expectations
<ul style="list-style-type: none">• Publicly available data not separated by time series	<ul style="list-style-type: none">• Focus efforts on static classification as opposed to feature registration
<ul style="list-style-type: none">• Publicly available data only has image data; patient records are not linked	<ul style="list-style-type: none">• Train model using larger amounts of training data and make inferences solely on images
<ul style="list-style-type: none">• Formatting image data took longer than expected	<ul style="list-style-type: none">• Spent time on standardizing data so image input to model would be clean



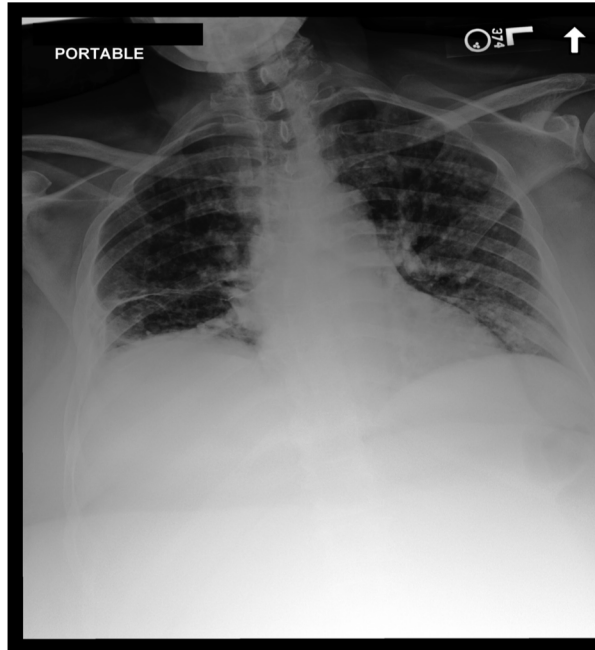
Chest X-ray Dataset Characteristics

	path	view	No Finding	Enlarged Cardiome-diastinum	Cardiomegal	Airspace Opacity	Lung Lesion	Edema	Consolidation	Pneumonia	Atelectasis	Pneumothor; Pleural Effusion	Pleural Other	Fracture	Support Devices
2	valid/p10228846/s01/view1_frontal.jpg	frontal	1												
3	valid/p10228846/s01/view2_lateral.jpg	lateral	1												
4	valid/p10228846/s02/view1_frontal.jpg	frontal				1				1					
5	valid/p10228846/s02/view2_lateral.jpg	lateral				1				1					
6	valid/p10248350/s01/view1_frontal.jpg	frontal	1												
7	valid/p10248350/s01/view2_lateral.jpg	lateral	1												
8	valid/p10275579/s01/view1_frontal.jpg	frontal				1			-1	-1			-1		
9	valid/p10275579/s01/view2_lateral.jpg	lateral				1			-1	-1			-1		
10	valid/p10275579/s01/view3_lateral.jpg	lateral				1			-1	-1			-1		
11	valid/p10275579/s02/view1_frontal.jpg	frontal								1			1		
12	valid/p10275579/s02/view2_lateral.jpg	lateral								1			1		
13	valid/p10296197/s01/view1_frontal.jpg	frontal	1												1

- Labels are annotated by researchers with up to 14 different thoracic pathology labels using automatic extraction methods on radiology reports
- Purposes of experiment: *use only frontal images*
- MIMIC and NIH datasets cleanly divided into *training* and *validation*
- Need JHMI data for testing



Example: Pneumonia vs. No Pneumonia

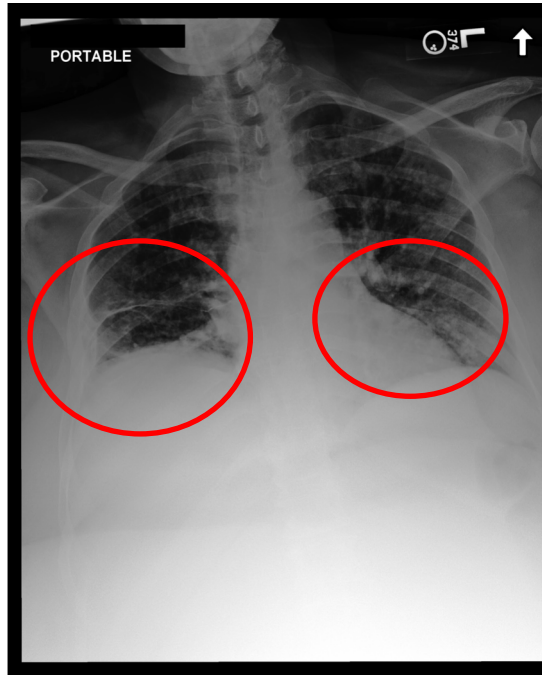


Patient with pneumonia



Patient without Pneumonia

Example: Pneumonia vs. No Pneumonia

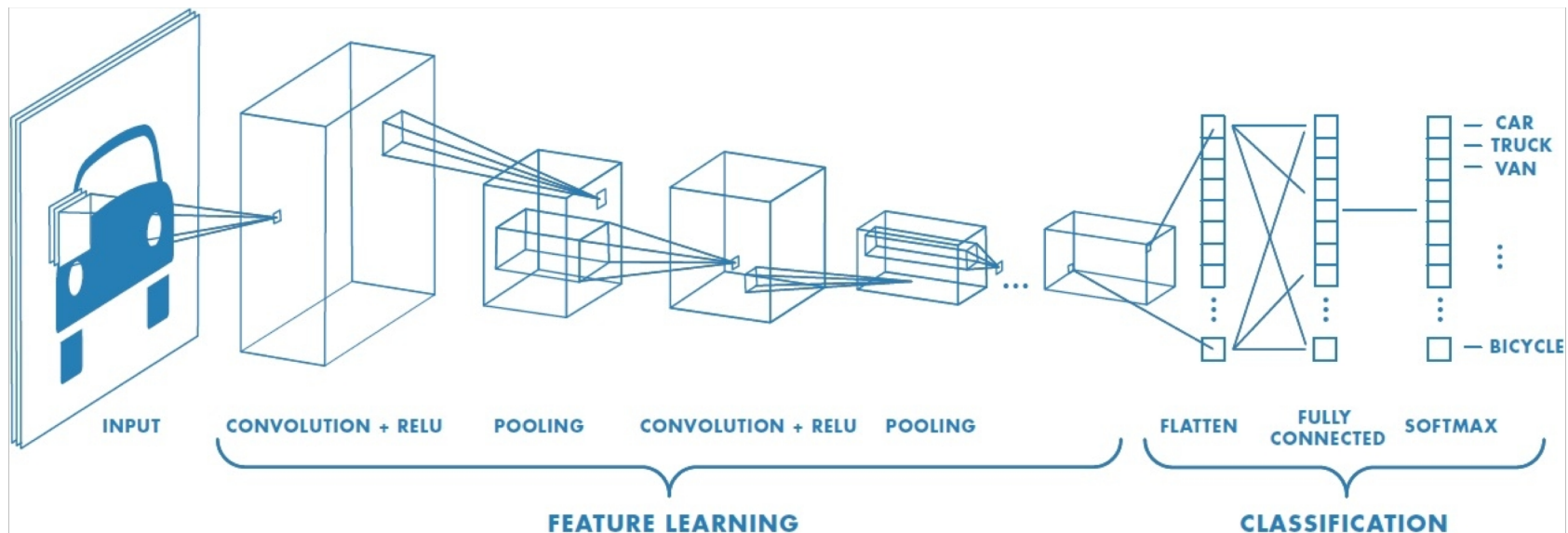


Patient with pneumonia



Patient without Pneumonia

CNN Architecture for ImageNet Models



- Transfer Learning: apply and finetune performance from pre-trained models to current dataset
- Use best-in-class CNNs: VGG, DenseNet, ResNet
- Augment with GPU on MARCC for optimized speed



Working Binary Classifier: Determining Pneumonia

- Initial Training Set Size: 2700 images → working up to 58K images
- Validation Set Size: 1700 images
- Best Model: VGG16 & ResNet
- Performance: .94 accuracy

Network Parameters for Binary Classification	
Loss Function	Binary Cross Entropy Loss
Optimization Function	SGD (stochastic gradient descent)
Output Activation Function	Probabilistic Softmax
Iterations	50
Epochs	5



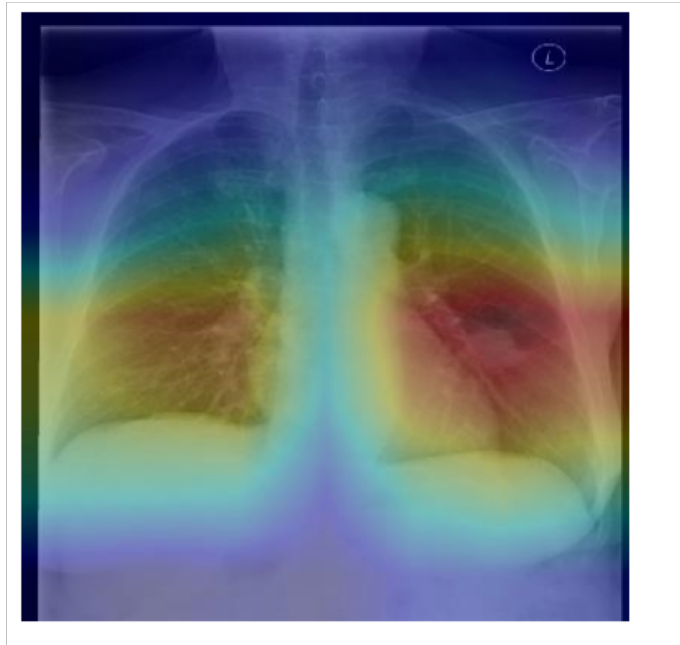
Working 3-Class Classifier

- Objective: can the model distinguish general thoracic diseases vs. pneumonia
- Initial Training Set Size: 58,000 images
- Validation Set Size: 1700 images
- Best Model: ResNet
- Performance: .68

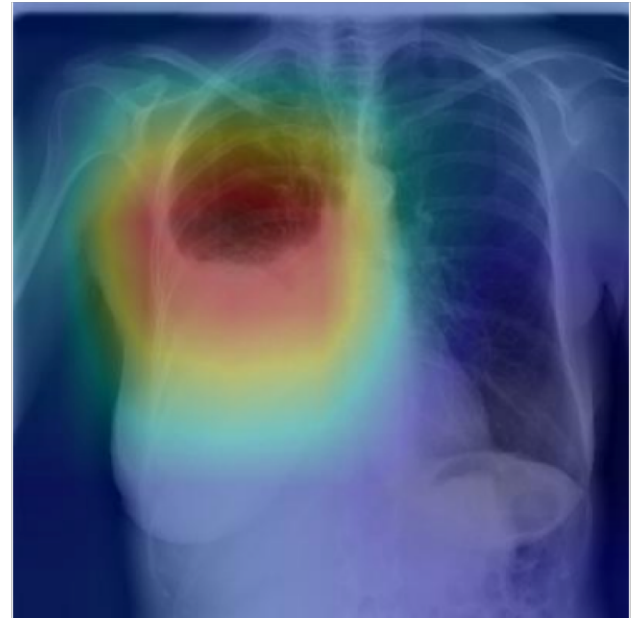
Network Parameters for 3-Class Classification	
Loss Function	Cross Entropy Loss
Optimization Function	SGD (stochastic gradient descent)
Dropout Rate	0.2
Output Activation Function	Probabilistic Softmax
Iterations	50
Epochs	3



Next Steps: Saliency Mapping & Class Activation Maps

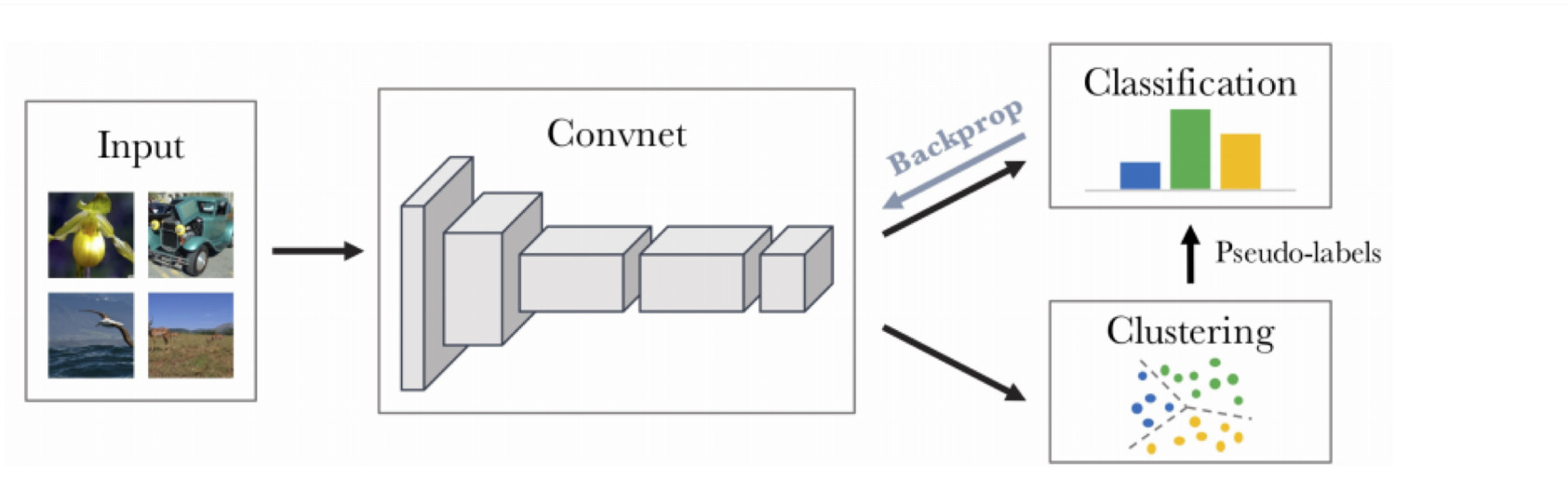


Patient with lower left lung nodule⁴



Patient with large right pleural effusion⁴

Next Steps: Unsupervised Learning



- Recently released findings (March 2019) on the Deep Cluster algorithm
- Groups the features with a standard clustering algorithm, kmeans, and uses the subsequent assignments as supervision to update the weights of the network³
- Able to find meaningful features in large-scale image datasets³

Updated Dependencies

Dependency	Solution	Status	Effect if not Complete
Access to MIMICS and NIH Datasets	Complete HIPAA training modules	Completed	Cannot start model training
Access to powerful GPU	Work on GPU through MARCC	Completed	Model training will take much longer
Access to MARCC	Request through Dr. Unberath	Completed	Data hosting will have to be local
Access to ImageNet models	Download through internet	Completed	Cannot start model training
IRB Approval for JHMI PICU Data	Request through clinical PIs	Ongoing: Expected by 4/28	Cannot validate on PICU images



Key Dates

- **4/19:** Robust multi-class classifier
- **4/22:** Completed saliency mapping and class activation map on training data
- **4/29:** Trained algorithm for unsupervised learning
- **5/5:** Test binary model against clinic data gathered from JHMI PICU; prepare into clinically actionable report
- **5/8:** Present project and finalize classification report



References

1. Caron, Mathilde, Piotr Bojanowski, Armand Joulin, and Matthijs Douze. "Deep Clustering for Unsupervised Learning of Visual Features." Mar. 2019. Facebook AI Research. Available at: <https://arxiv.org/pdf/1807.05520.pdf> Accessed 10 Apr. 2019.
2. Hatami, N., Gavet, Y. and Debayle, J. (2019). *Classification of Time-Series Images Using Deep Convolutional Neural Networks*. [online] arXiv.org. Available at: <https://arxiv.org/abs/1710.00886>. Accessed 20 Feb. 2019.
3. Kollef, M. H., Dr. (2005). WHAT IS VENTILATOR-ASSOCIATED PNEUMONIA AND WHY IS IT IMPORTANT? *Respiratory Care*, 50(6), 714-724. Accessed February 26, 2019.
4. Rajpurkar, Pranav, and Jeremy Irvin. "CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning." Dec. 2017. Stanford University. Available at: <https://arxiv.org/pdf/1711.05225.pdf>. Accessed 15 Mar. 2019.

