

Nal Kalchbrenner Google Research Amsterdam, Brain team



#### MetNet Team







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Jonathan Heek



Jason Hickey



**Daniel Furrer** 



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Mostafa Dehghani



Lak Lakshmanan



Tim Salimans



Stephan Hoyer



Carla Bromberg



Dirk Weissenborn



John Burge



Zack Ontiveros



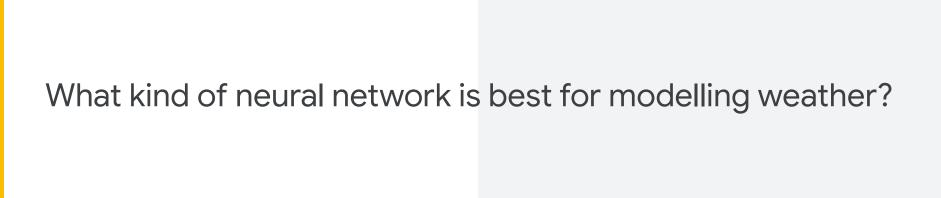
Aaron Bell



Nal Kalchbrenner







#### **Neural Weather Models**

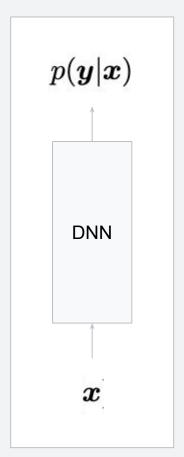
#### **Neural Weather Models**

- Probabilistic models
- Spatiotemporal structure
- Discrete distributions

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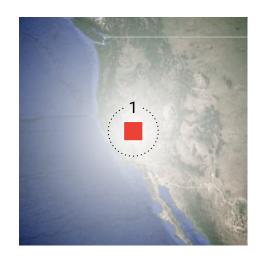
- Probabilistic models
- Spatiotemporal structure
- Discrete distributions

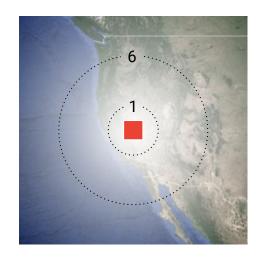
#### (Probabilistic) DNNs

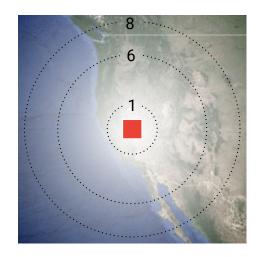


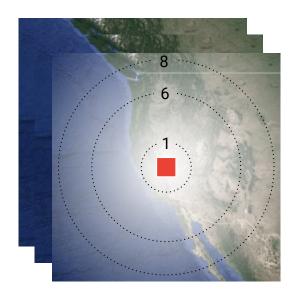


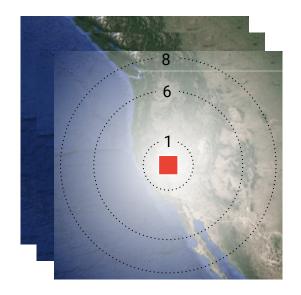




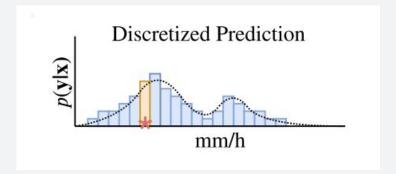


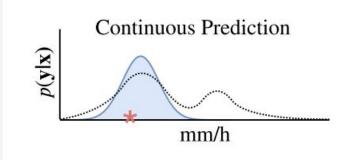


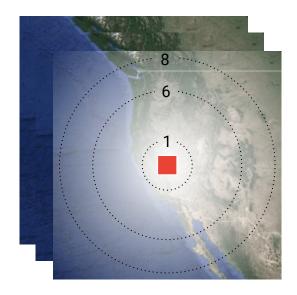




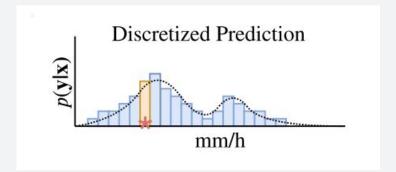
#### Discrete Variables



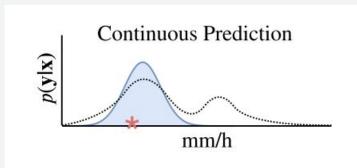


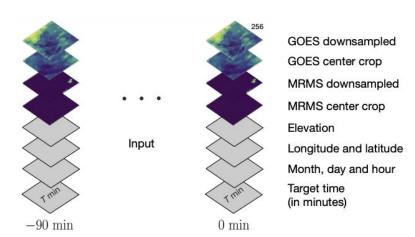


#### Discrete Variables

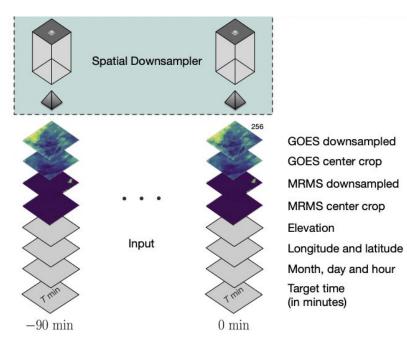


[0.0, 0.2, 0.4, 0.6, ..., 100.0]

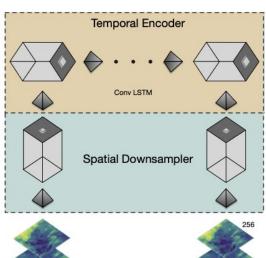


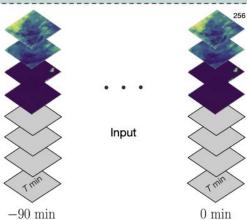






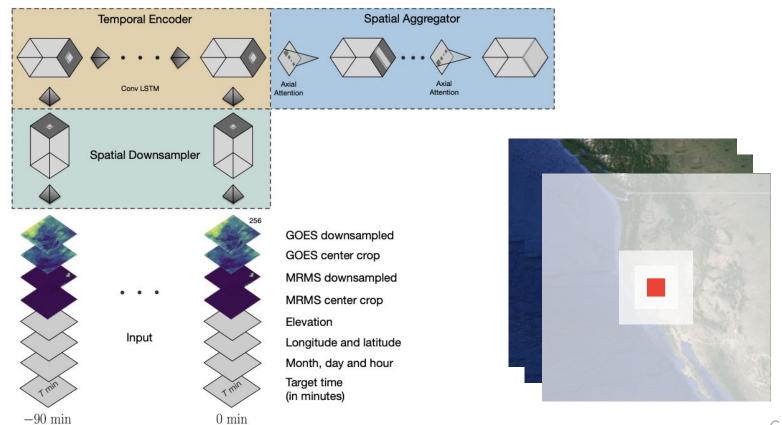


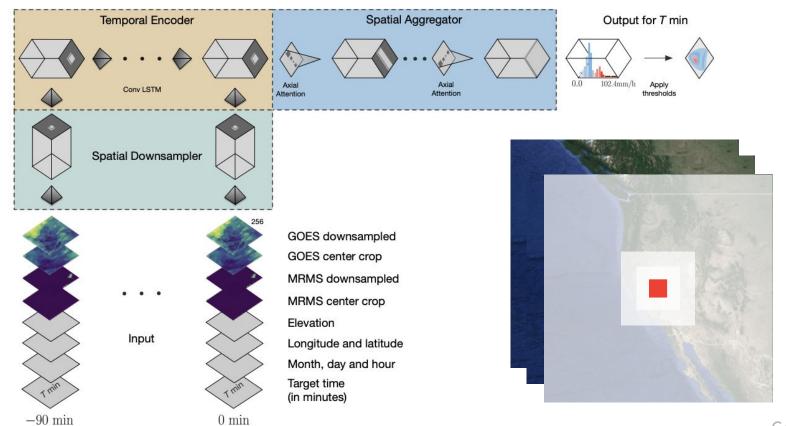




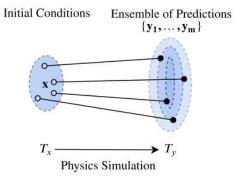
GOES downsampled
GOES center crop
MRMS downsampled
MRMS center crop
Elevation
Longitude and latitude
Month, day and hour
Target time
(in minutes)



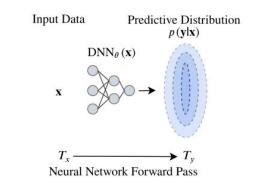




# **Numerical Weather Prediction Neural Weather Models**

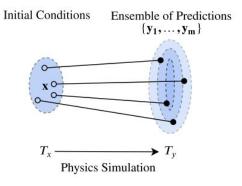


#### **Numerical Weather Prediction**

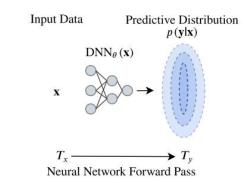


#### **Neural Weather Models**

Uncertainty through ensembling	mbling Uncertainty from direct probabilistic model	

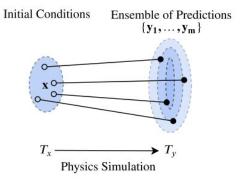


#### **Numerical Weather Prediction**



#### **Neural Weather Models**

Uncertainty through ensembling Uncertainty from direct probabilistic mode		
Relies on equations of physics	Relies on generic learnable transformations (and requires data)	



# $x \longrightarrow T_y$ Neural Network Forward Pass

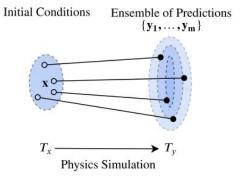
Input Data

#### **Numerical Weather Prediction**

**Neural Weather Models** 

Predictive Distribution  $p(\mathbf{y}|\mathbf{x})$ 

Uncertainty through ensembling	Uncertainty from direct probabilistic model
Relies on equations of physics	Relies on generic learnable transformations (and requires data)
Latency of prediction is generally linear as a function of lead time	Latency of prediction is constant (or logarithmic) as a function of lead time. MetNet takes under a second for any lead time of up to 8 hours



# Input Data Predictive Distribution $p(\mathbf{y}|\mathbf{x})$ $\mathbf{x} \qquad \qquad \qquad \mathbf{T}_{x} \qquad \qquad \mathbf{T}_{y}$ Neural Network Forward Pass

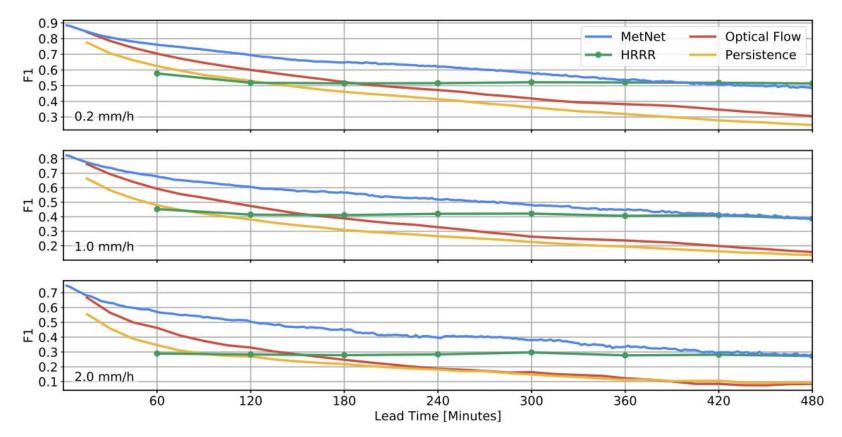
#### **Numerical Weather Prediction**

**Neural Weather Models** 

Uncertainty through ensembling	Uncertainty from direct probabilistic model	
Relies on equations of physics	Relies on generic learnable transformations (and requires data)	
Latency of prediction is generally linear as a function of lead time	Latency of prediction is constant (or logarithmic) as a function of lead time. MetNet takes under a second for any lead time of up to 8 hours	
Accuracy depends on underlying resolution.  Doubling resolution requires ~ 8 times more computation.	Accuracy does not depend on underlying resolution.  Doubling resolution requires ~ 4 times more computation.	

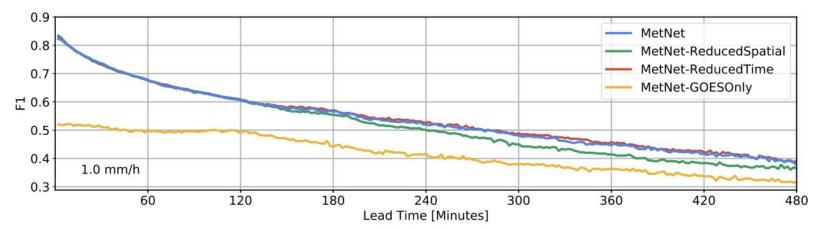
#### Results

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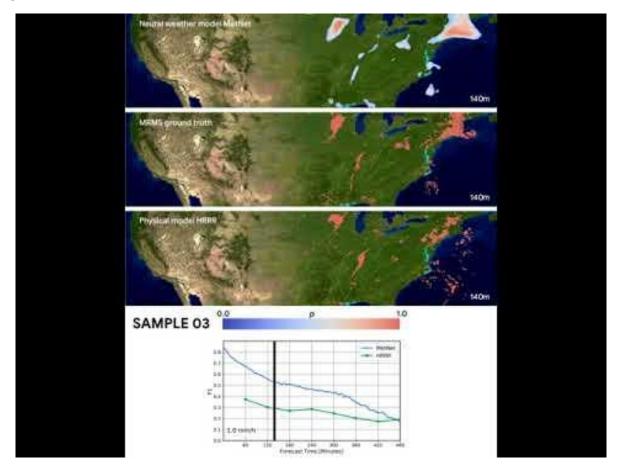


#### **Ablation Results**

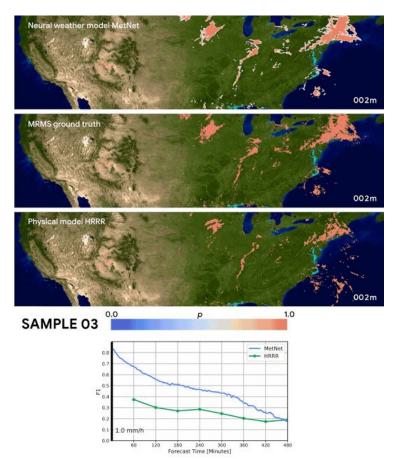
Configuration	Spatial Context (km)	<b>Temporal Context (min)</b>	<b>Data Sources</b>
MetNet	1024	90	MRMS, GOES-16
MetNet-ReducedSpatial	512	90	MRMS, GOES-16
MetNet-ReducedTemporal	1024	30	MRMS, GOES-16
MetNet-GOESOnly	1024	90	GOES-16



# Sampled predictions



# Sampled predictions



## Prospects

