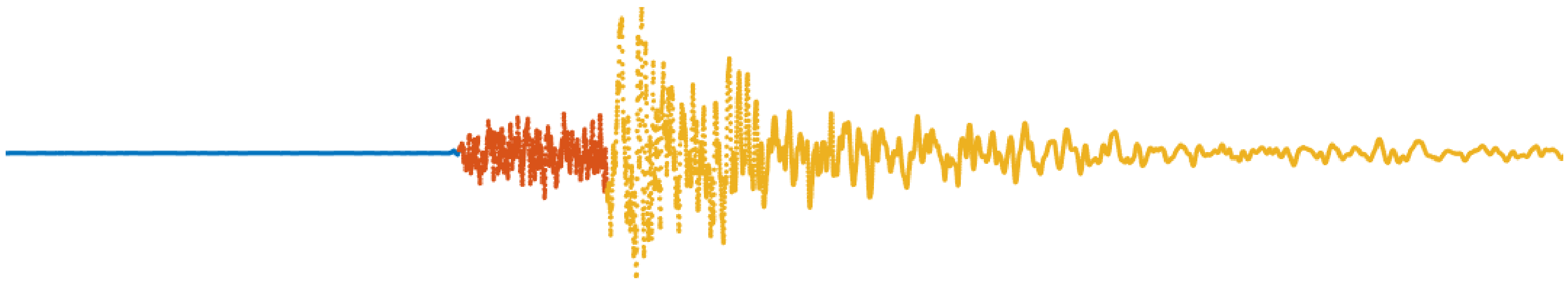
Using LSTM network to identify P- and S-wave arrivals in seismic data



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Joyeeta Mukherjee
Conor Daly
Mathworks

Cautionary Note

The companies in which Royal Dutch Shell plc directly and indirectly owns investments are separate legal entities. In this presentation “Shell”, “Shell group” and “Royal Dutch Shell” are sometimes used for convenience where references are made to Royal Dutch Shell plc and its subsidiaries in general. Likewise, the words “we”, “us” and “our” are also used to refer to Royal Dutch Shell plc and subsidiaries in general or to those who work for them. These terms are also used where no useful purpose is served by identifying the particular entity or entities. ‘‘Subsidiaries’’, “Shell subsidiaries” and “Shell companies” as used in this presentation refer to entities over which Royal Dutch Shell plc either directly or indirectly has control. Entities and unincorporated arrangements over which Shell has joint control are generally referred to as “joint ventures” and “joint operations”, respectively. Entities over which Shell has significant influence but neither control nor joint control are referred to as “associates”. The term “Shell interest” is used for convenience to indicate the direct and/or indirect ownership interest held by Shell in an entity or unincorporated joint arrangement, after exclusion of all third-party interest.

This presentation contains forward-looking statements (within the meaning of the U.S. Private Securities Litigation Reform Act of 1995) concerning the financial condition, results of operations and businesses of Royal Dutch Shell. All statements other than statements of historical fact are, or may be deemed to be, forward-looking statements. Forward-looking statements are statements of future expectations that are based on management’s current expectations and assumptions and involve known and unknown risks and uncertainties that could cause actual results, performance or events to differ materially from those expressed or implied in these statements. Forward-looking statements include, among other things, statements concerning the potential exposure of Royal Dutch Shell to market risks and statements expressing management’s expectations, beliefs, estimates, forecasts, projections and assumptions. These forward-looking statements are identified by their use of terms and phrases such as “aim”, “ambition’, ‘‘anticipate’’, ‘‘believe’’, ‘‘could’’, ‘‘estimate’’, ‘‘expect’’, ‘‘goals’’, ‘‘intend’’, ‘‘may’’, ‘‘objectives’’, ‘‘outlook’’, ‘‘plan’’, ‘‘probably’’, ‘‘project’’, ‘‘risks’’, “schedule”, ‘‘seek’’, ‘‘should’’, ‘‘target’’, ‘‘will’’ and similar terms and phrases. There are a number of factors that could affect the future operations of Royal Dutch Shell and could cause those results to differ materially from those expressed in the forward-looking statements included in this [report], including (without limitation): (a) price fluctuations in crude oil and natural gas; (b) changes in demand for Shell’s products; (c) currency fluctuations; (d) drilling and production results; (e) reserves estimates; (f) loss of market share and industry competition; (g) environmental and physical risks; (h) risks associated with the identification of suitable potential acquisition properties and targets, and successful negotiation and completion of such transactions; (i) the risk of doing business in developing countries and countries subject to international sanctions; (j) legislative, fiscal and regulatory developments including regulatory measures addressing climate change; (k) economic and financial market conditions in various countries and regions; (l) political risks, including the risks of expropriation and renegotiation of the terms of contracts with governmental entities, delays or advancements in the approval of projects and delays in the reimbursement for shared costs; and (m) changes in trading conditions. No assurance is provided that future dividend payments will match or exceed previous dividend payments. All forward-looking statements contained in this [report] are expressly qualified in their entirety by the cautionary statements contained or referred to in this section. Readers should not place undue reliance on forward-looking statements. Additional risk factors that may affect future results are contained in Royal Dutch Shell’s 20-F for the year ended December 31, 2019 (available at www.shell.com/investor and www.sec.gov). These risk factors also expressly qualify all forward looking statements contained in this presentation and should be considered by the reader. Each forward-looking statement speaks only as of the date of this presentation, November 17, 2020. Neither Royal Dutch Shell plc nor any of its subsidiaries undertake any obligation to publicly update or revise any forward-looking statement as a result of new information, future events or other information. In light of these risks, results could differ materially from those stated, implied or inferred from the forward-looking statements contained in this presentation.

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Project

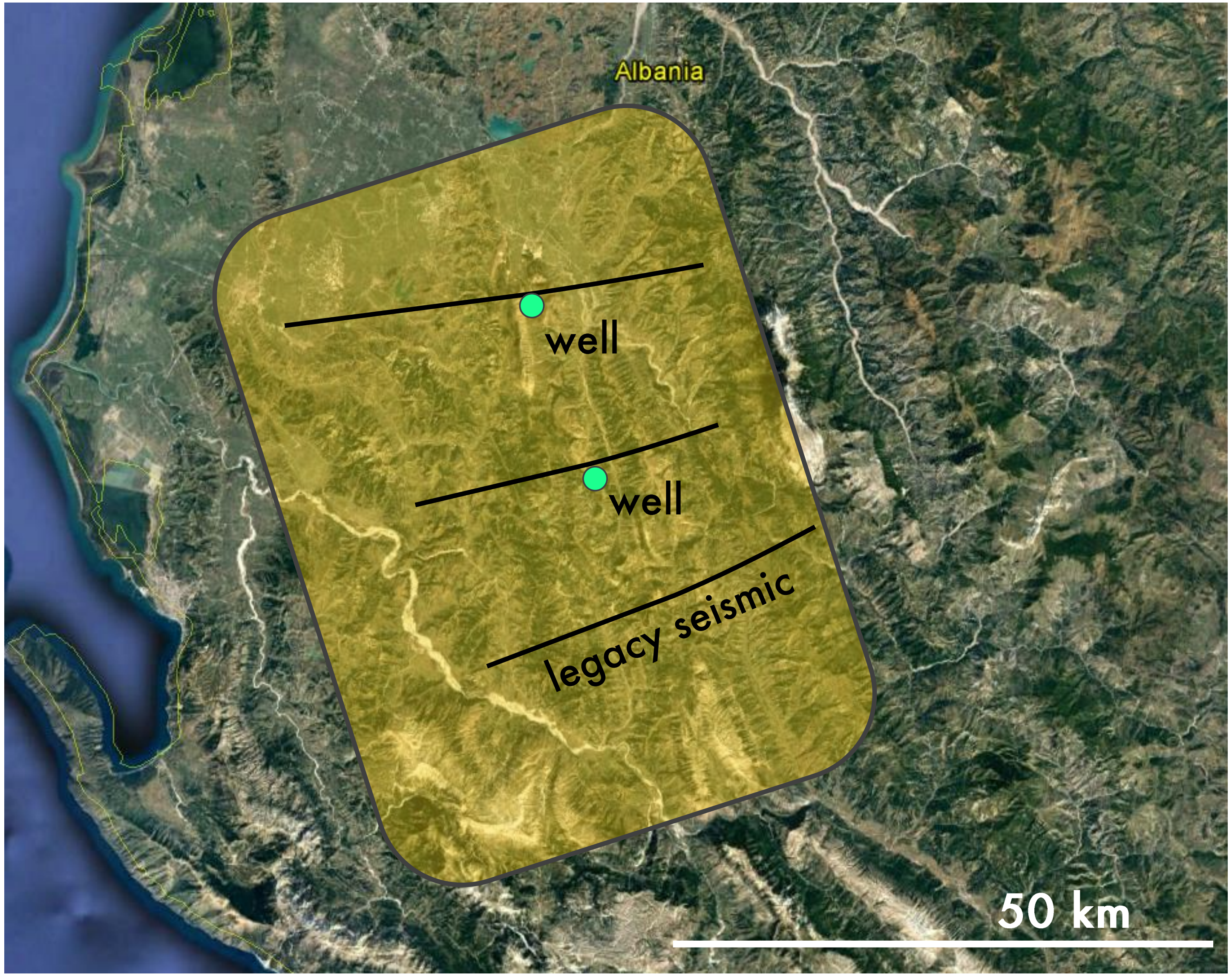
How to explore large basin efficiently with limited 1D-2D data?

Proposition:

Use passive sources of energy to image 3D volume and stitch together 1D-2D data.

Outcomes:

1. Quick (months not years)
2. Relatively cheap
3. Multiple data sets
4. Integrate all data in 3D
5. Sweet-spot basin
6. Environmentally friendly



Project

Gravity and magnetics

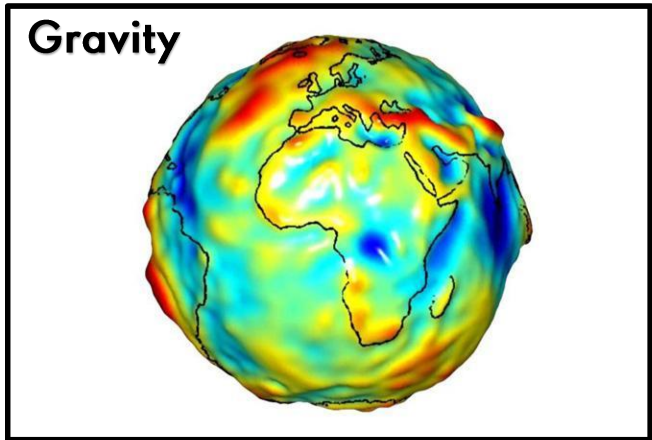
Solar wind and lightning

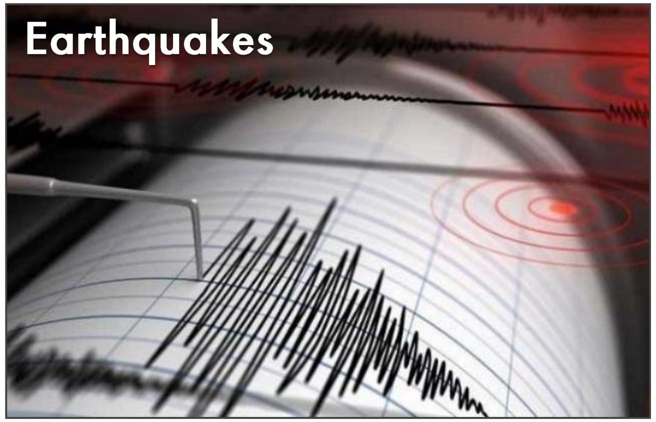
- Present everywhere
- MT used in industry many decades

Earthquakes and ocean noise

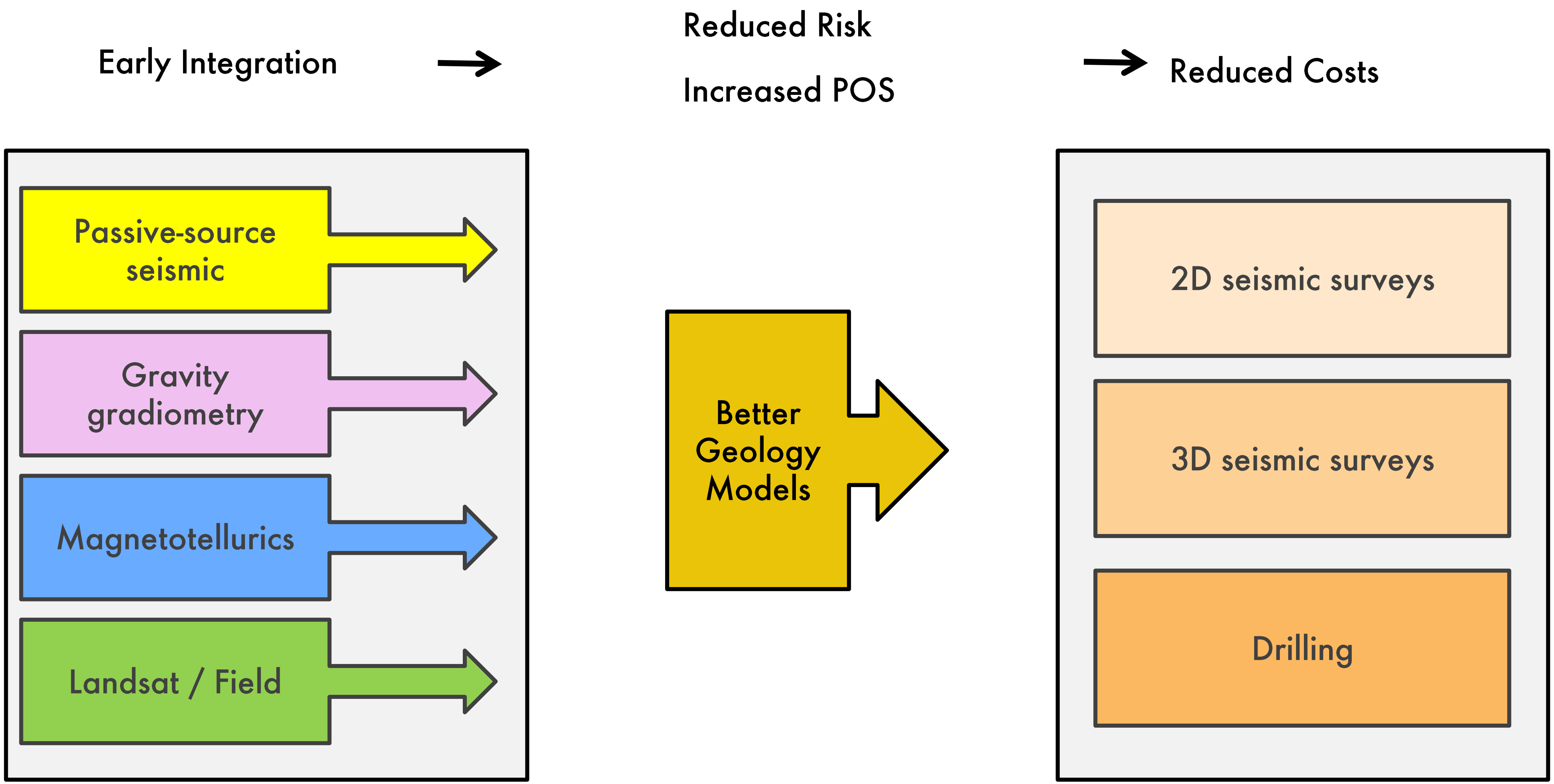
- Earthquakes image entire crust
- Ocean noise image upper crust

Human-generated noise



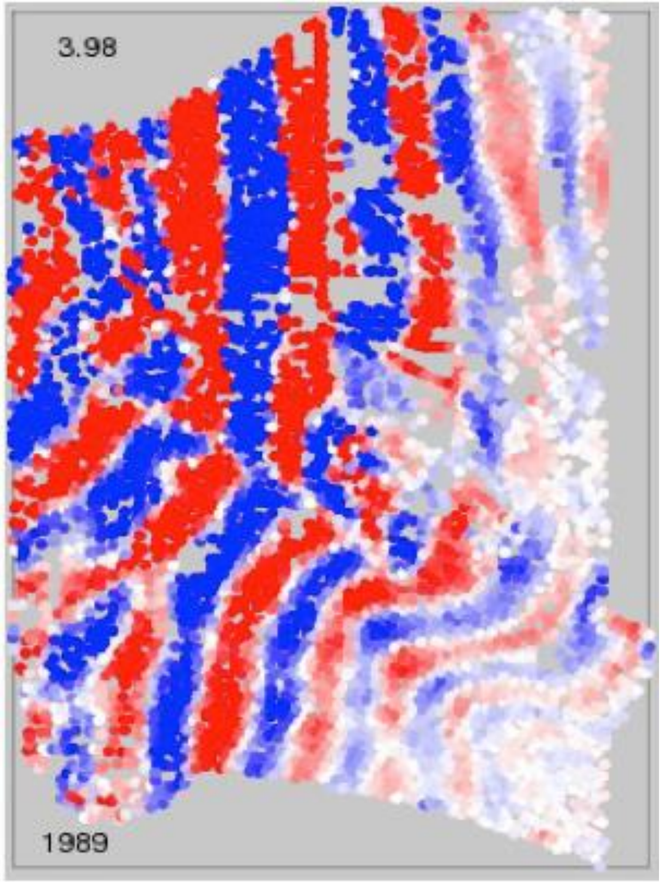


Project


Early Integration
Reduced Risk
Increased POS
Reduced Costs
Passive-source seismic
Gravity gradiometry
Magnetotellurics
Landsat / Field
Better Geology Models
2D seismic surveys
3D seismic surveys
Drilling

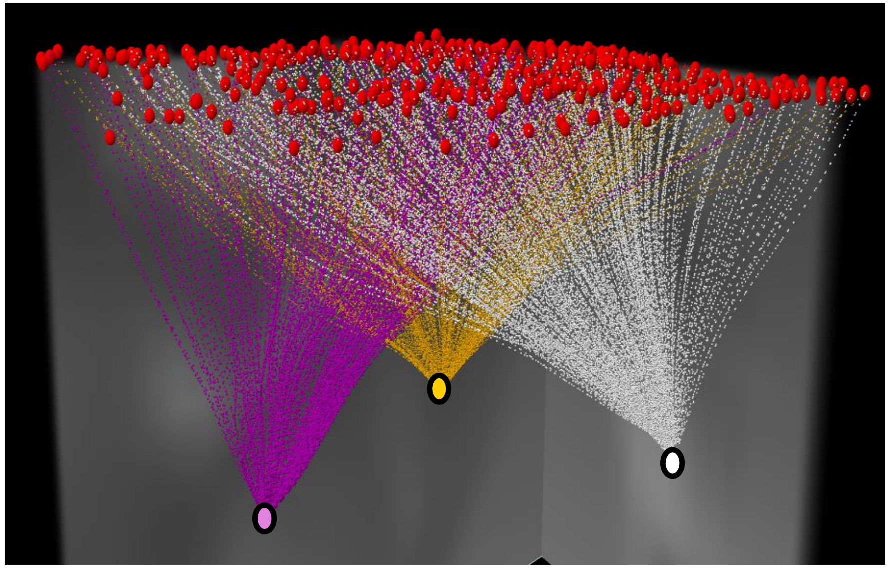
Project

One earthquake



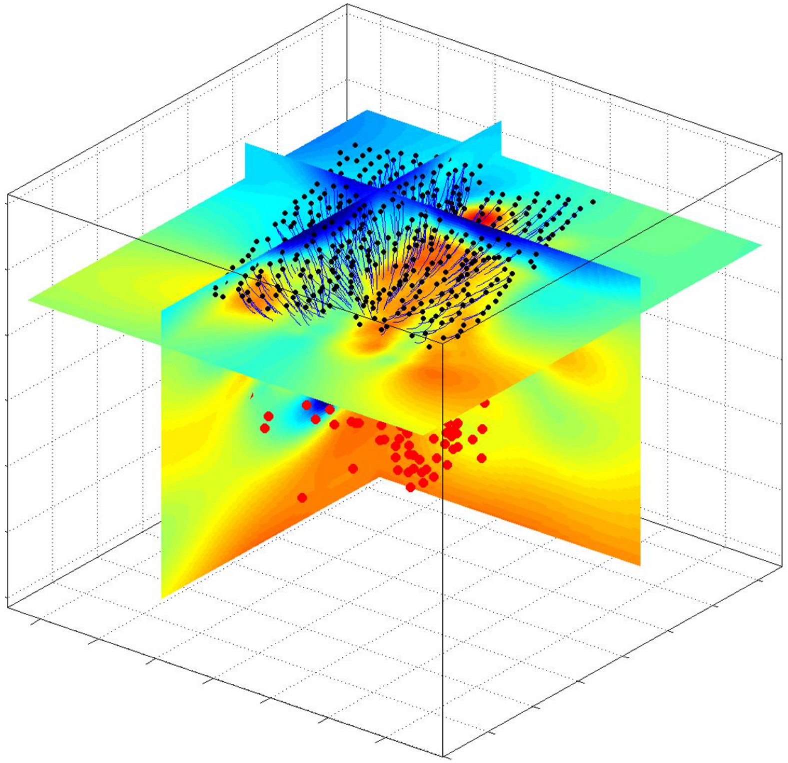
(Figures from Robert Clayton's CalTech web site)

Three earthquakes



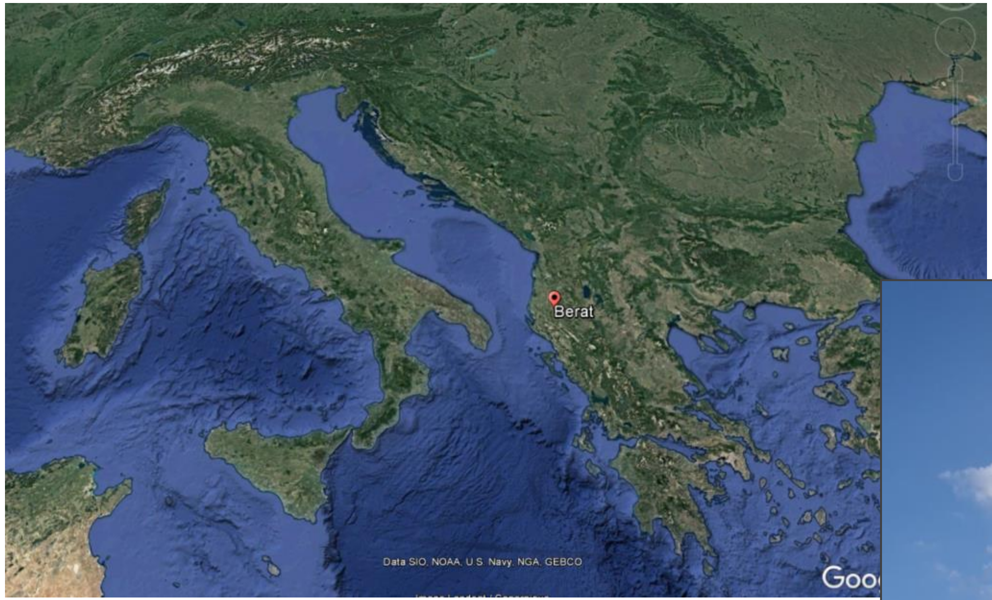
(# earthquakes) * (# nodes) = # raypaths

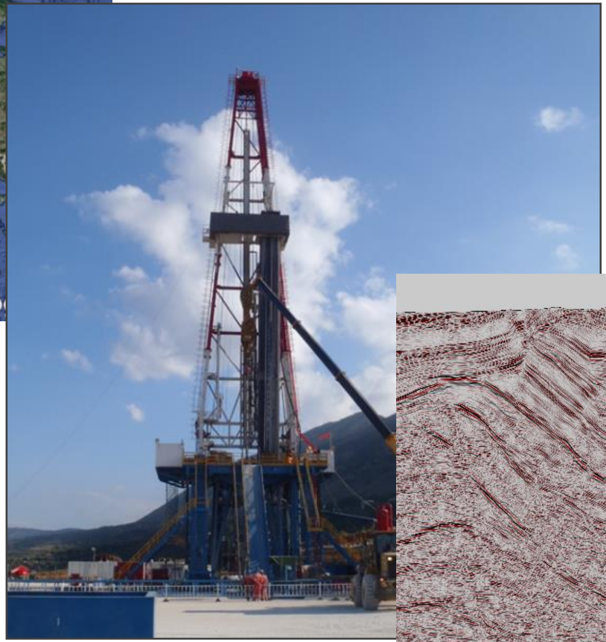
100s of earthquakes



Velocity cube derived from raypaths
(tomographic imaging)

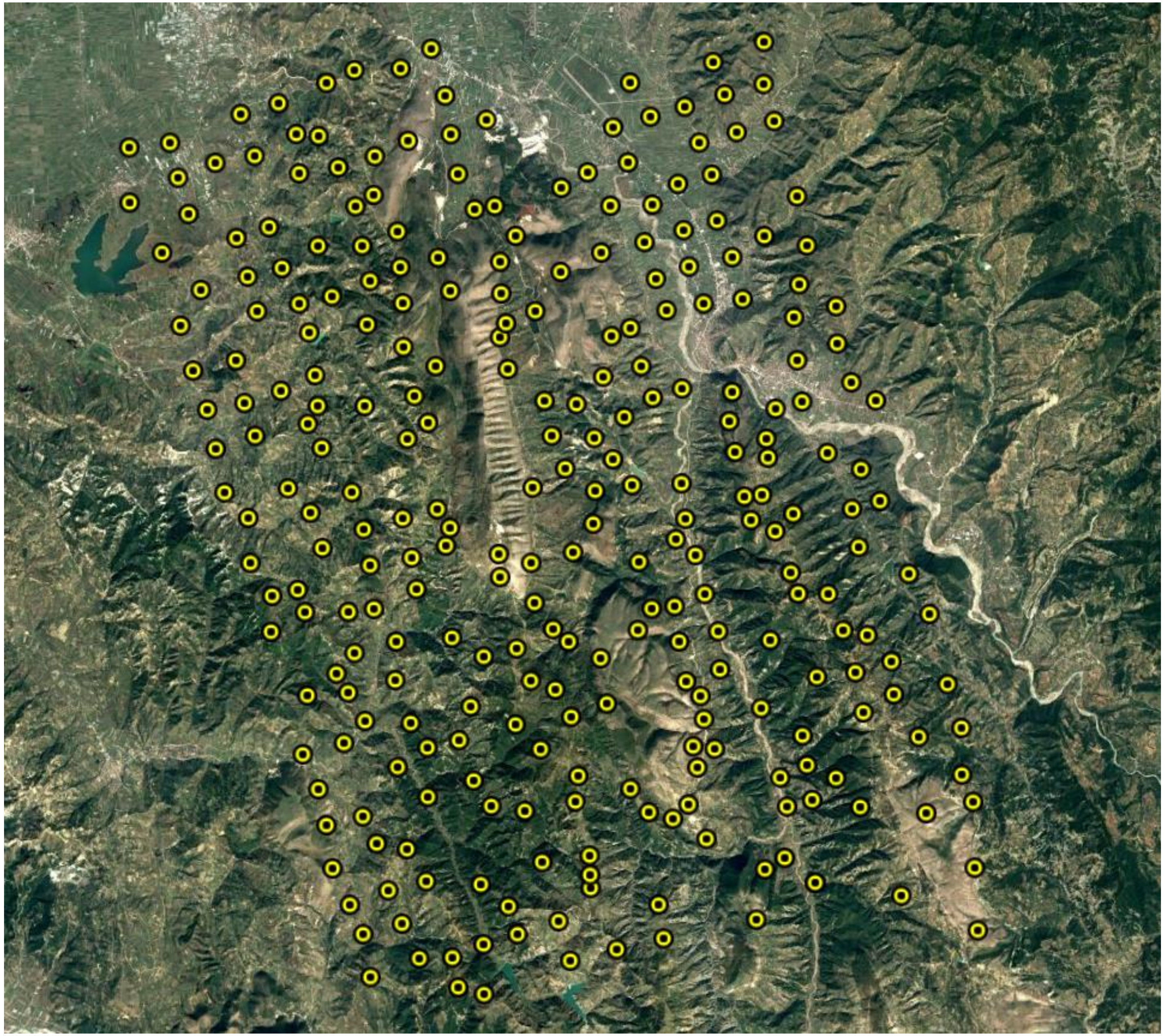
Project





Project

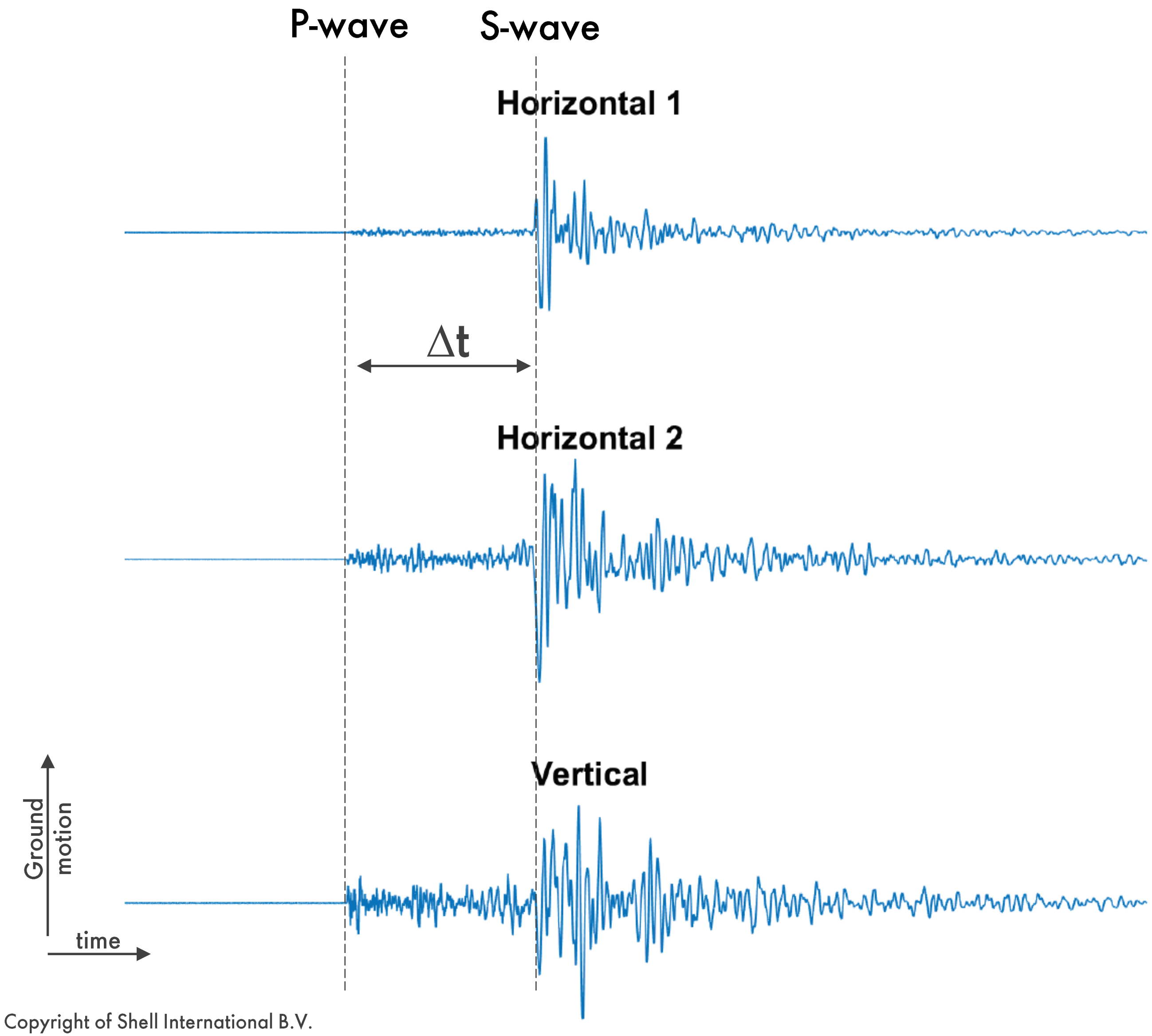
Project

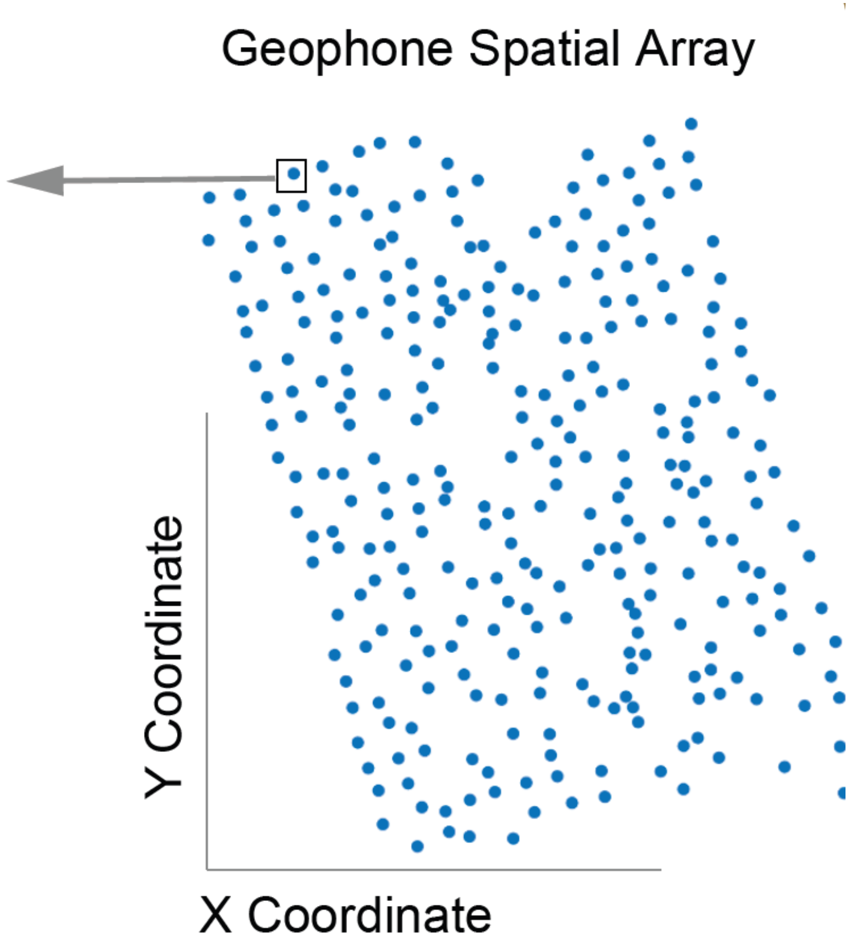


Regional Survey

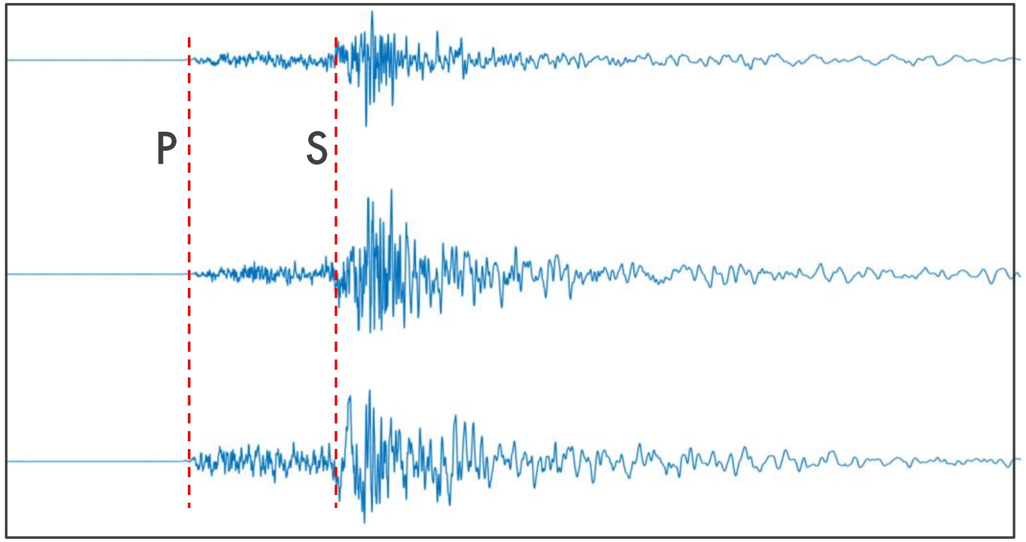
- 500 km^2 area
- 390 nodes
- 3 months

Data from one node



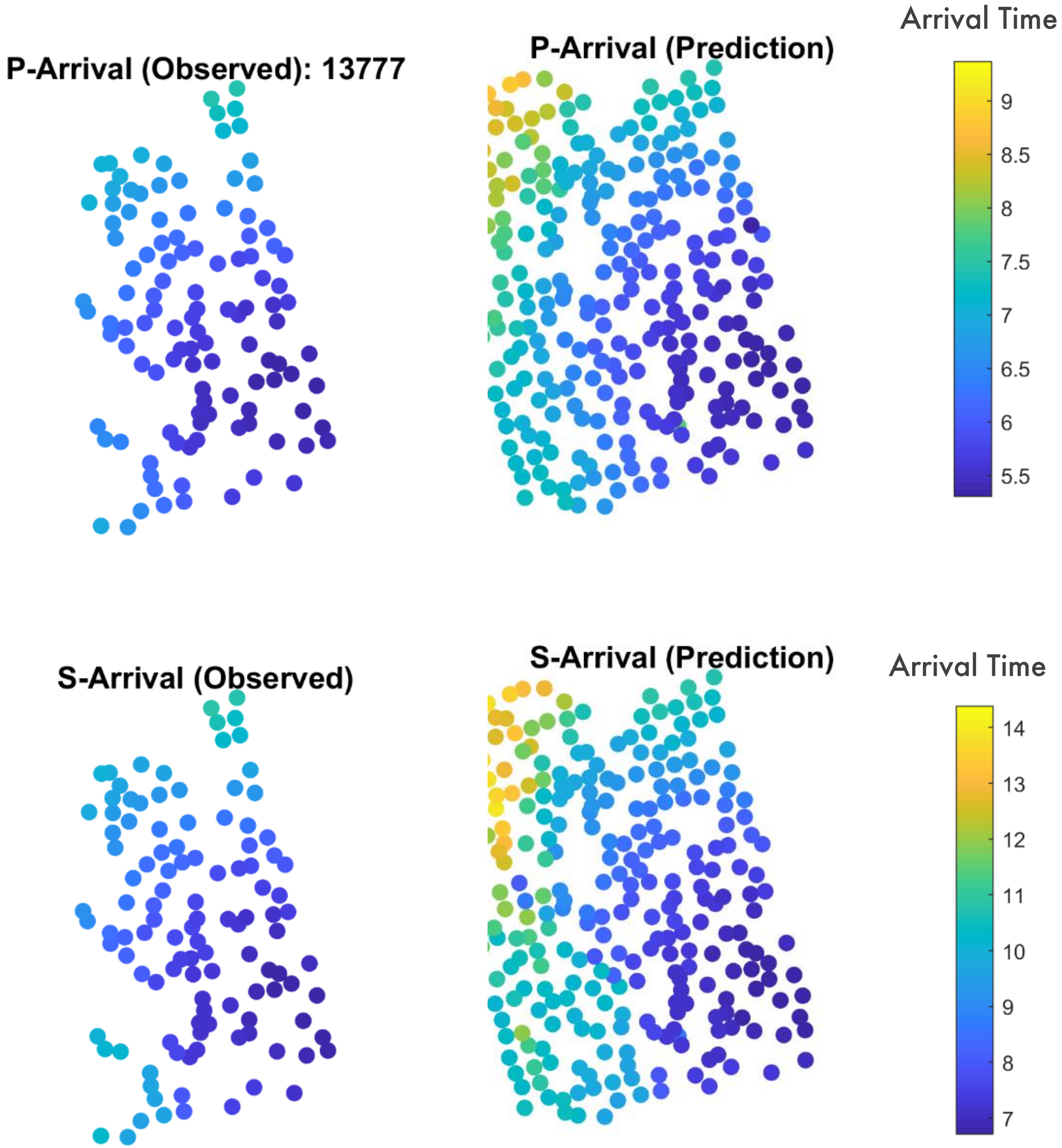


Problem



Extreme amount of data

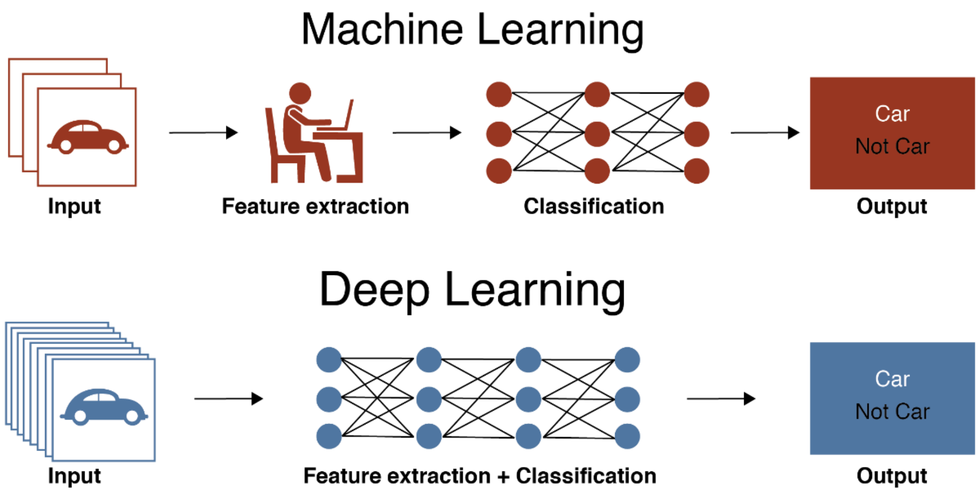
- 286 local earthquakes used in initial study
- 63,000 picks (+37k P-waves, +25k S-waves)
- Picked manually (> 5 months of effort)
- Much data from 286 left unpicked (> 68%)



Solution

Use a deep learning approach to problem

- Specialized form of machine learning
- Model learns directly from raw data
- Scales with data; avoids saturation
- Potential to use in other areas once trained



Turned to Mathwork's specialists

- Software readily accessible to novice
- Mathwork's staff are experienced in deep learning
- Shell already had working relations with Mathworks
- Staff very easy to work with and customer centric

Data preparation

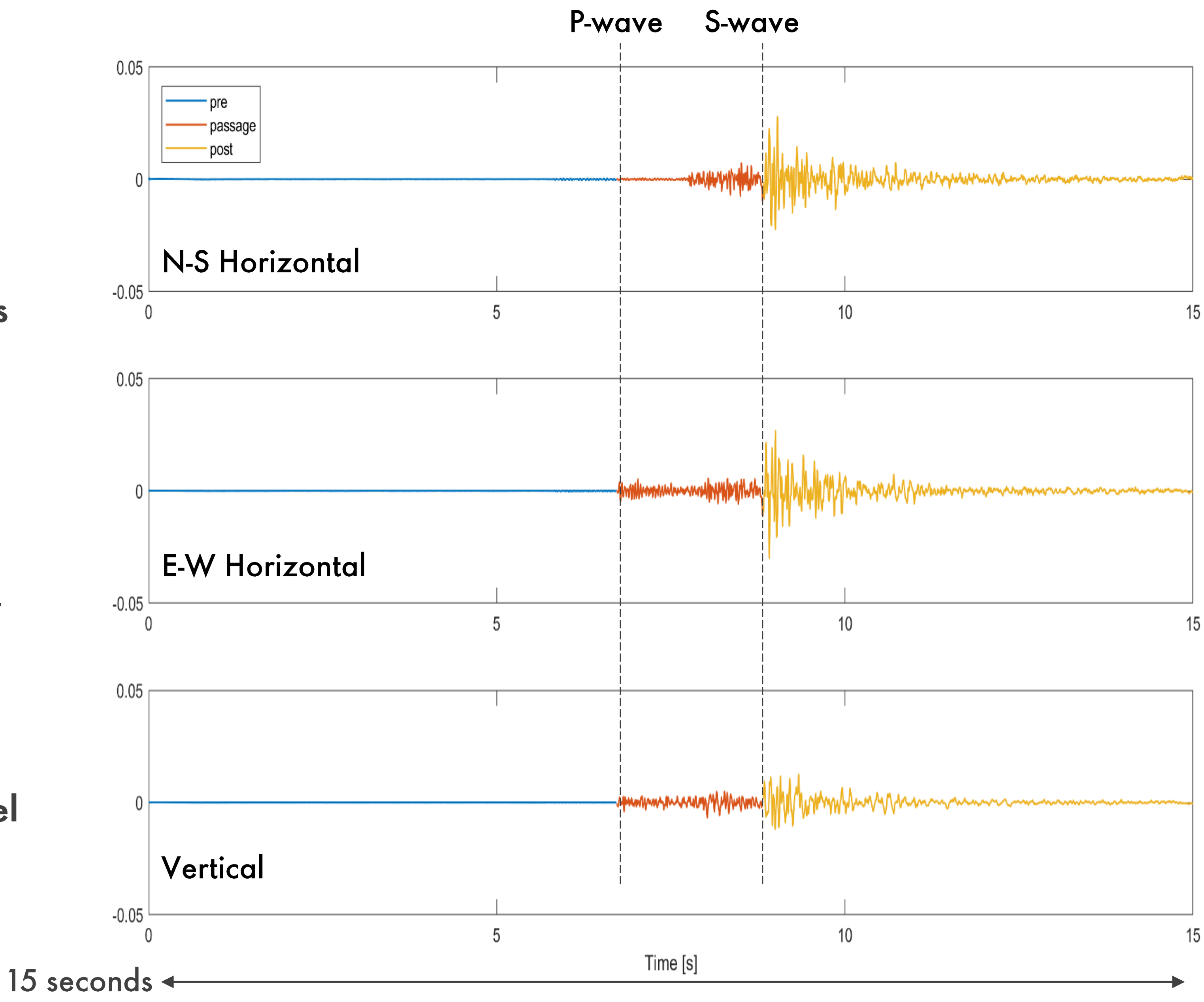
(1) Use 3 component data (=> 3 features)

(2) Parse continuous data into 15s intervals

(3) Divide signal into three classes

- Pre – signal prior to P-wave arrival
- Passage – signal between P- and S-wave arrivals
- Post – signal after S-wave arrival

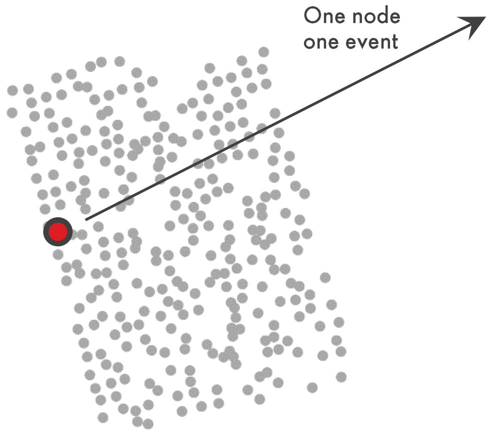
(4) Normalize amplitudes for each channel

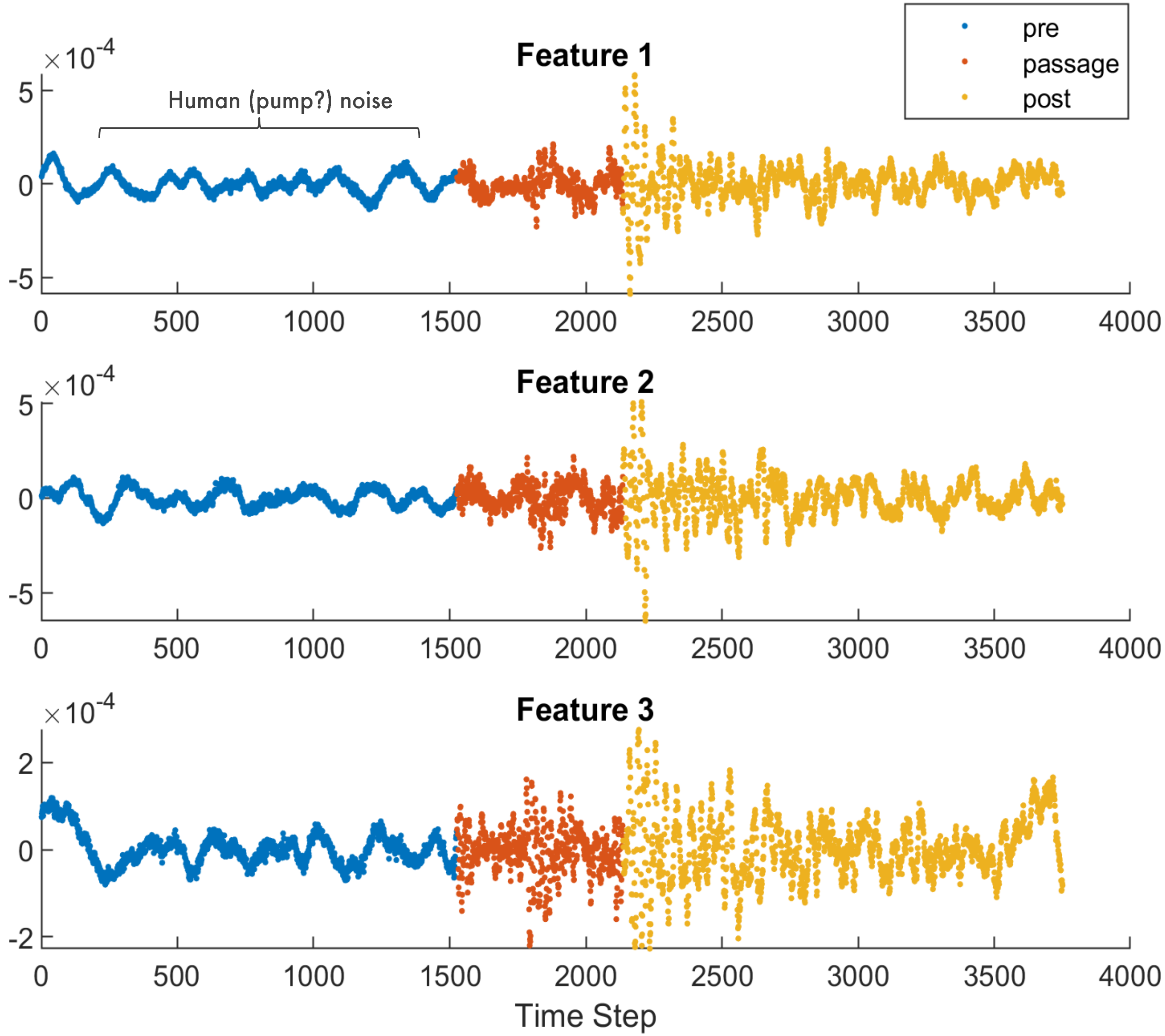


Data preparation

(5) Use data with different signals

- Variable signal-to-noise ratios
- Anthropogenic noise
- Strong events, weak events
- Variable frequency content
- Two different instruments
- Location of earthquakes

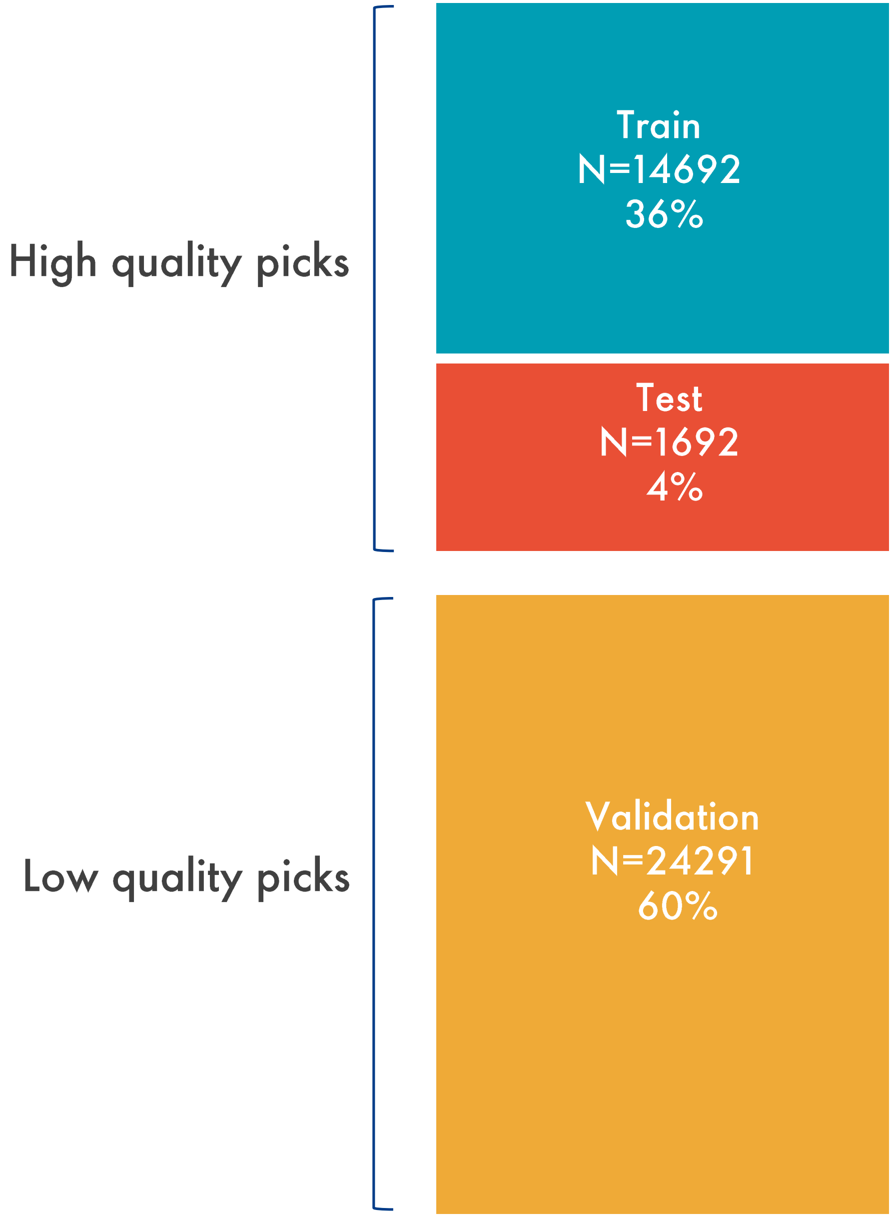




Data preparation

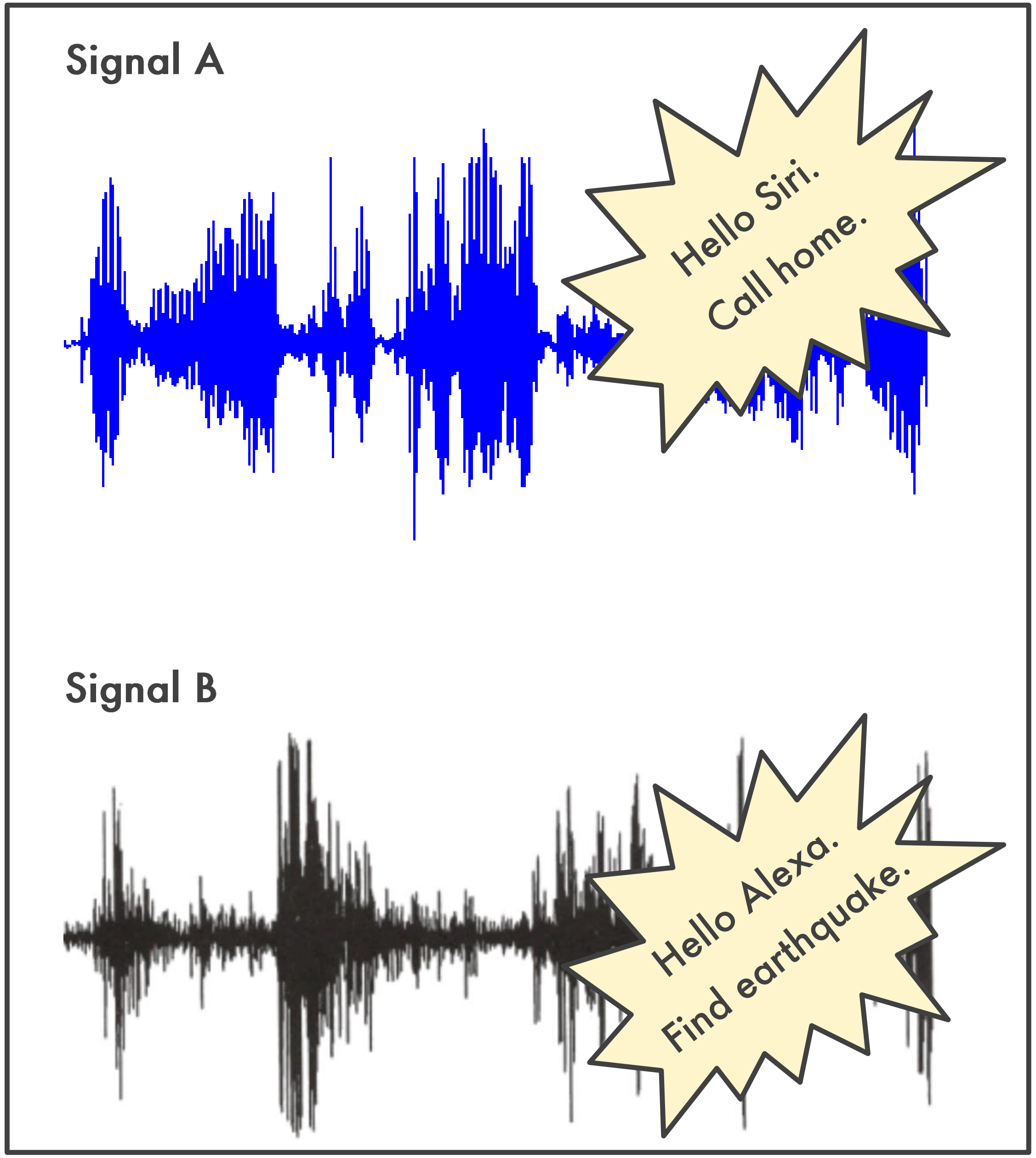
(6) Subset data

- Training set – used to train network
- Test set – used during training to modify hyperparameters
- Validation set – not used in training. Analyzed after training to determine how well the network performs.



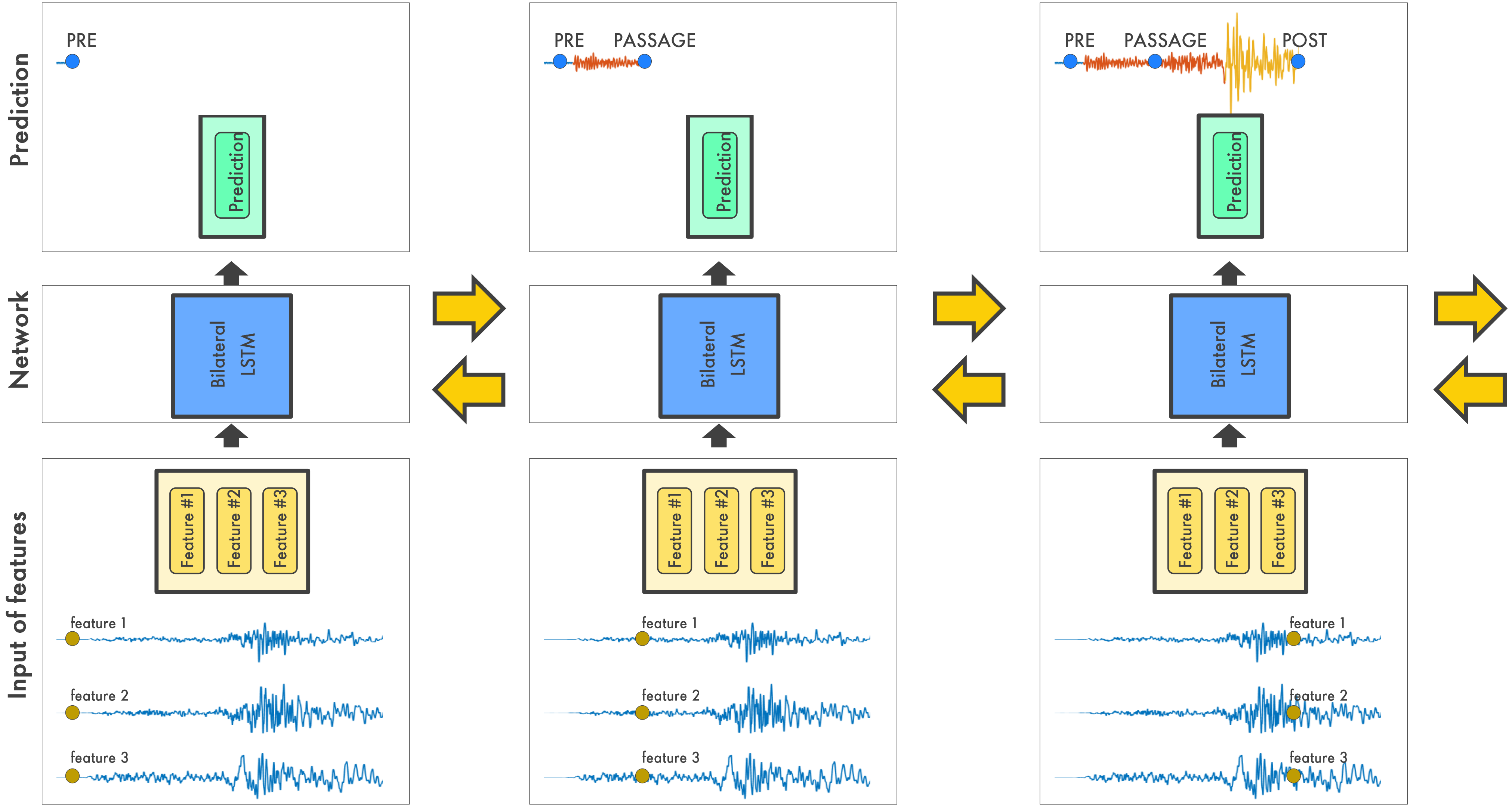
Network selection

- Mathwork's staff quickly realized similarities between the earthquake data and human speech!
- Long Short-Term Memory (LSTM)
  - Handles time-series data.
  - Long time durations with no signal, punctuated by short bursts of signal.
  - Uses information from far in the "past" and "present" time frame, hence the reason for the "Long" and "Short" in the name.
  - Used for speech recognition (Amazon Alexa, Apple Siri, Google Translate).

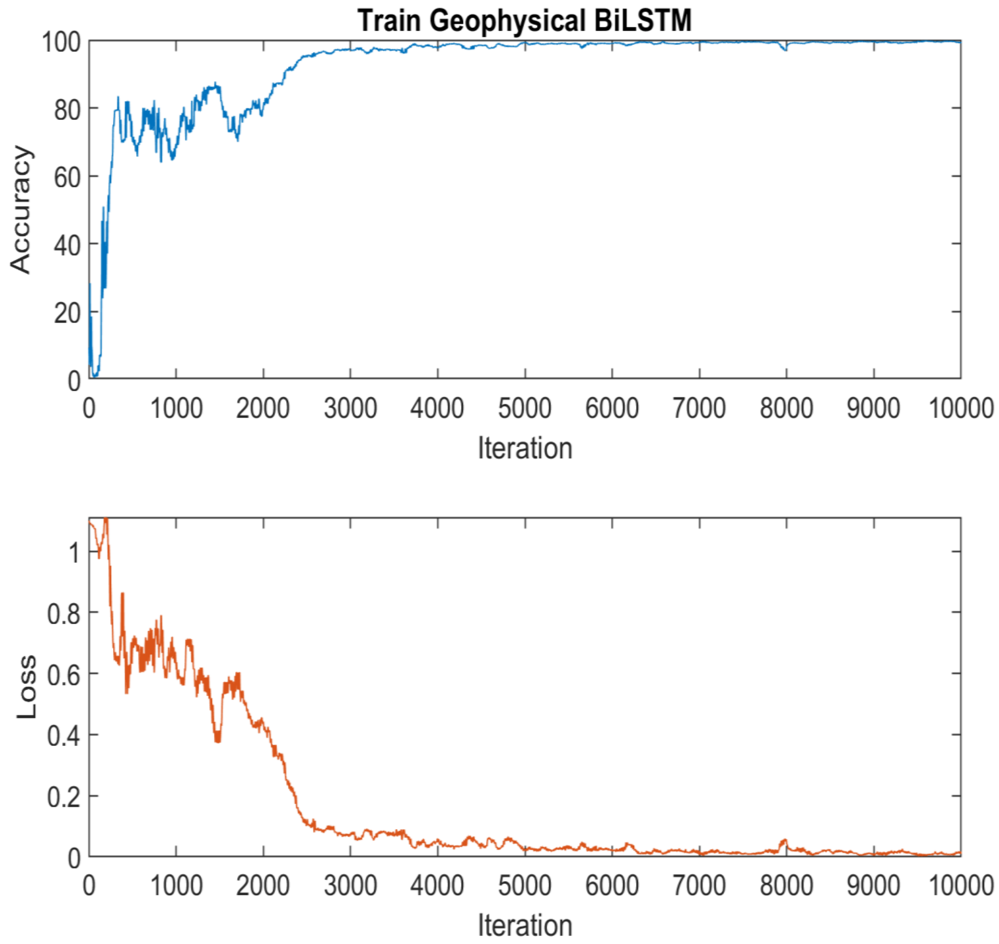


Network selection

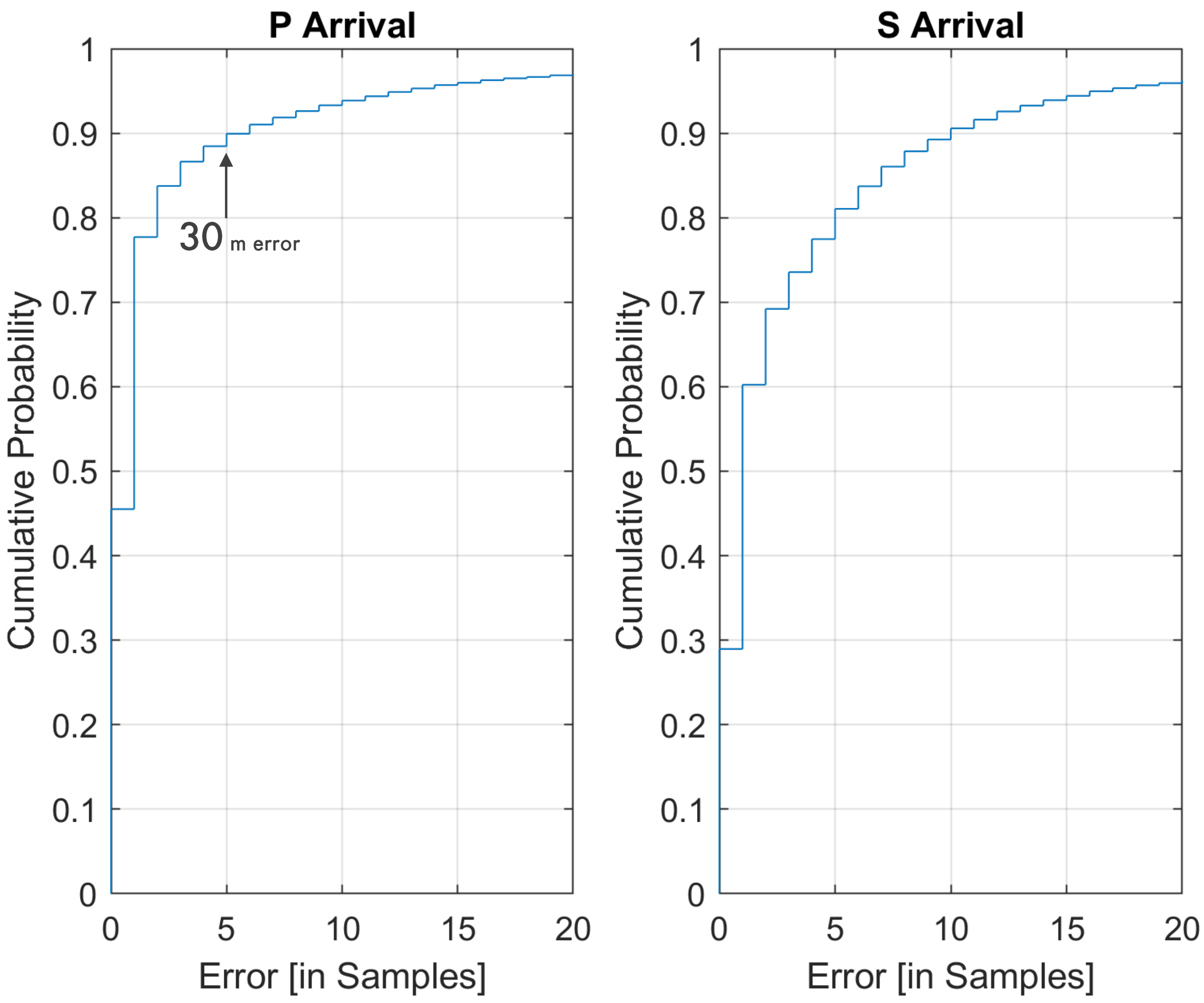
bilateral LSTM (location in sequence is "remembered" in network)



Results



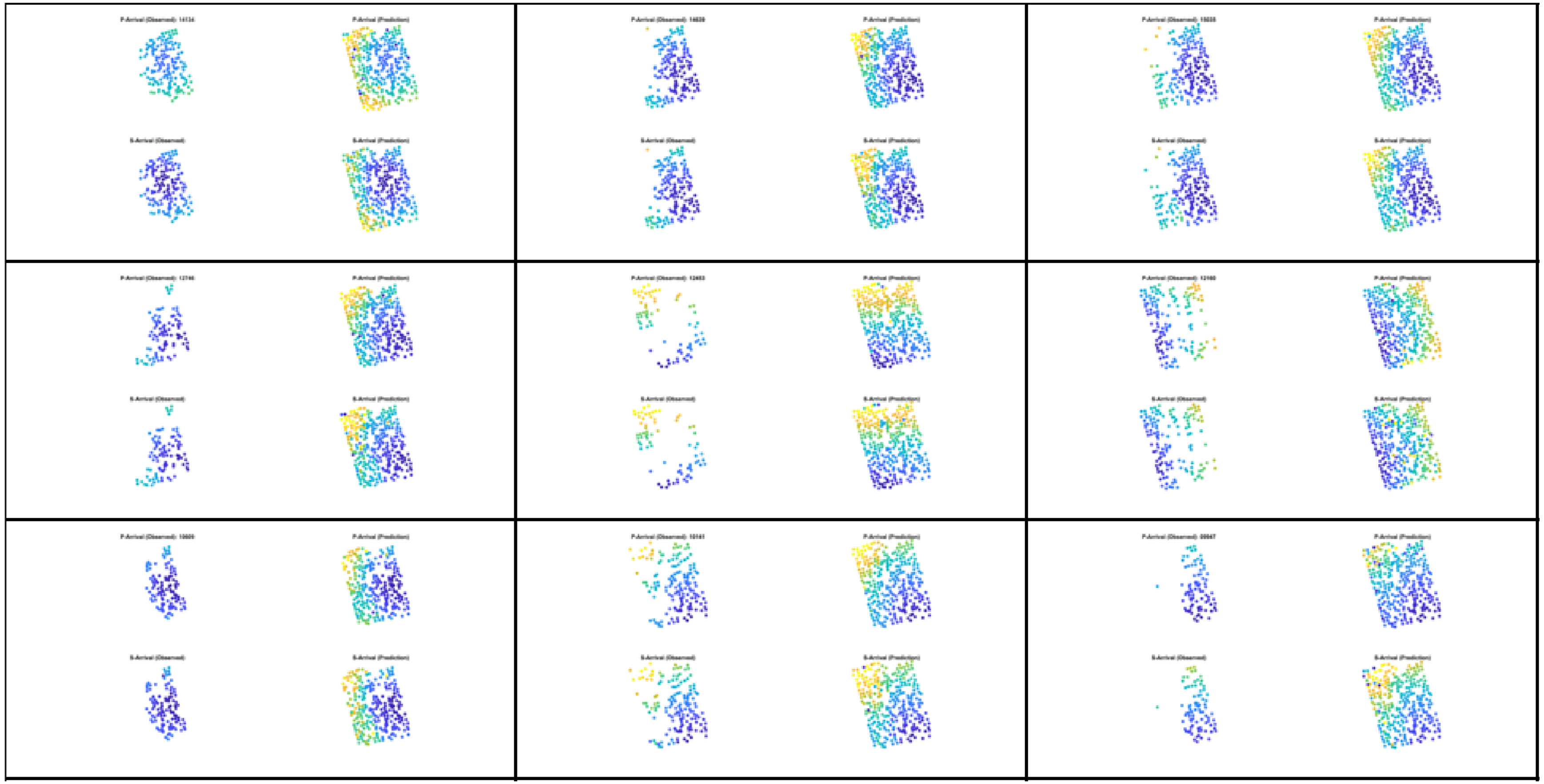
Train Geophysical BiLSTM
Accuracy
100
80
60
40
20
0
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000
Iteration
Loss
1
0.8
0.6
0.4
0.2
0
Iteration



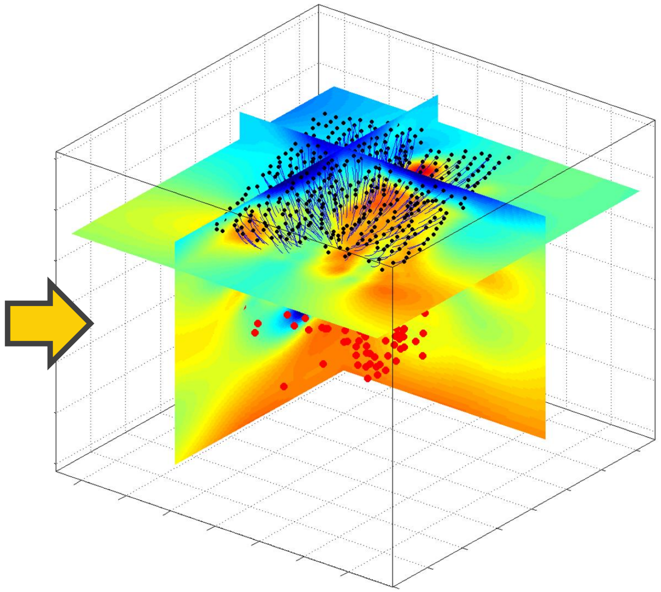
P Arrival
30 m error
Cumulative Probability
Error [in Samples]
S Arrival
Cumulative Probability
Error [in Samples]

Results

Results from 9 earthquakes



Final product is velocity model (geology model)



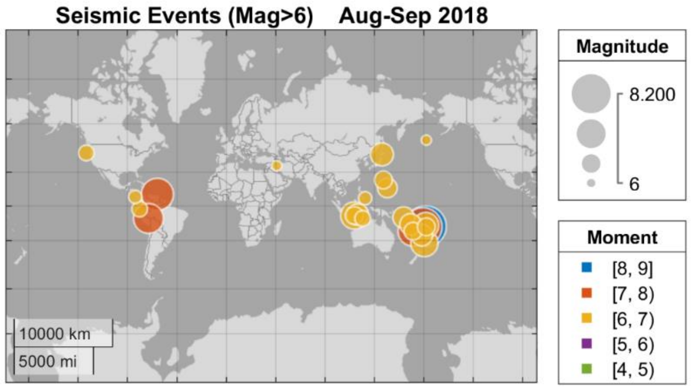
Generalization

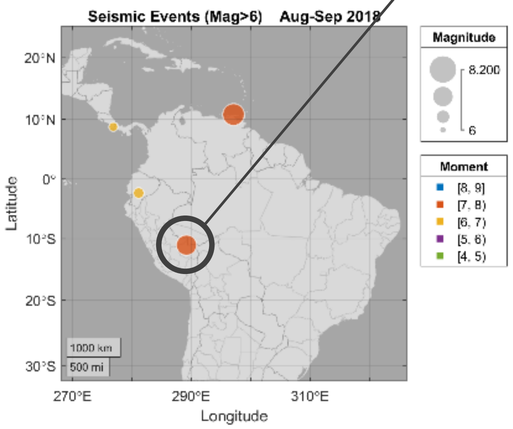
Generalization – Global Earthquakes

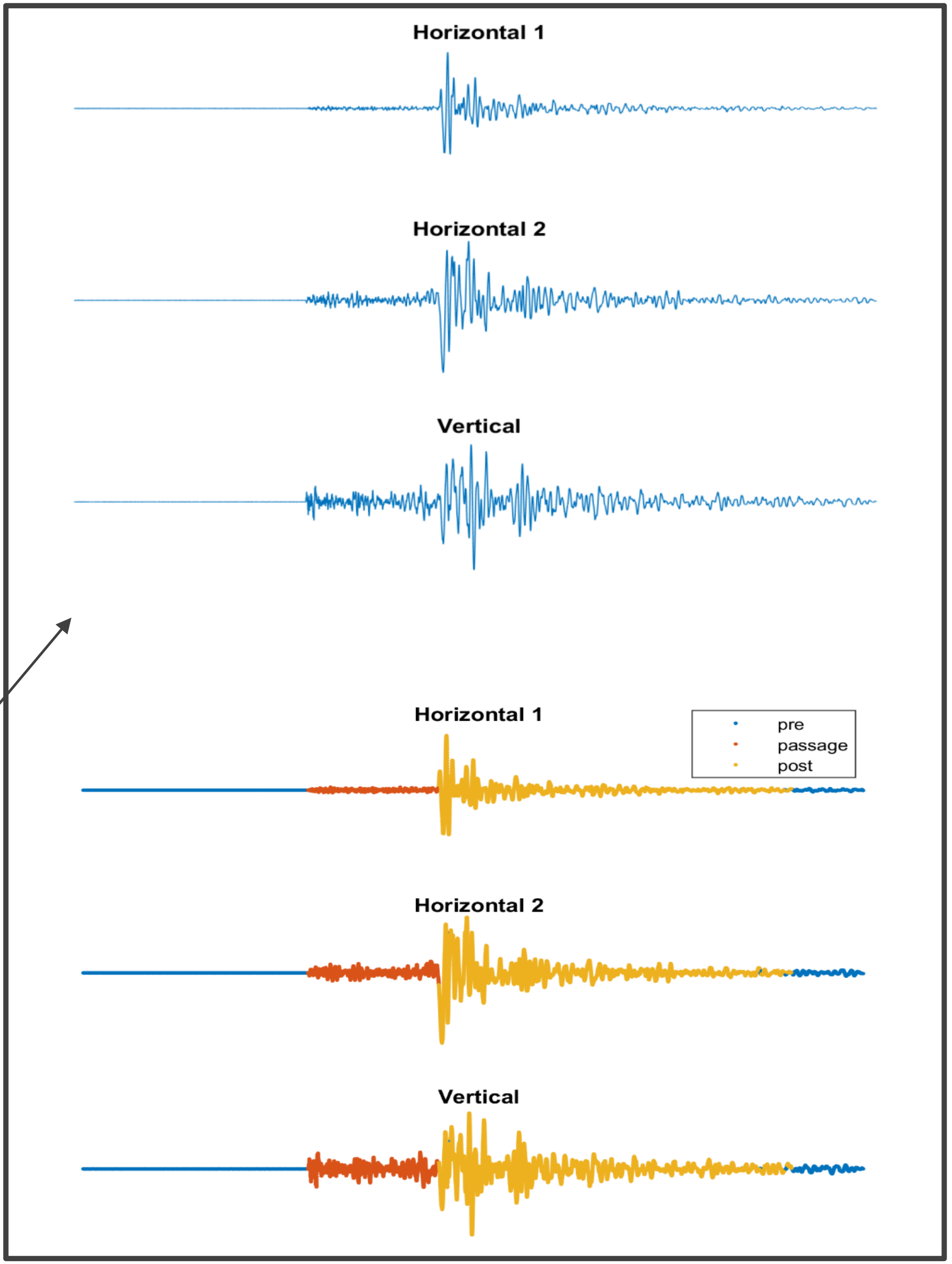
Can network trained on Albania earthquakes accurately detect "global" earthquakes?

What's Different?

1. Geology
2. Instrumentation
3. Duration: 10sec vs 8min
4. Depth: 10km vs 100km
5. Magnitude <1 Mb vs >4 Mb







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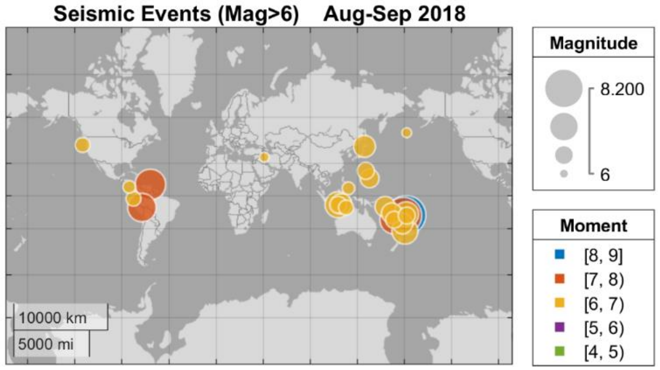
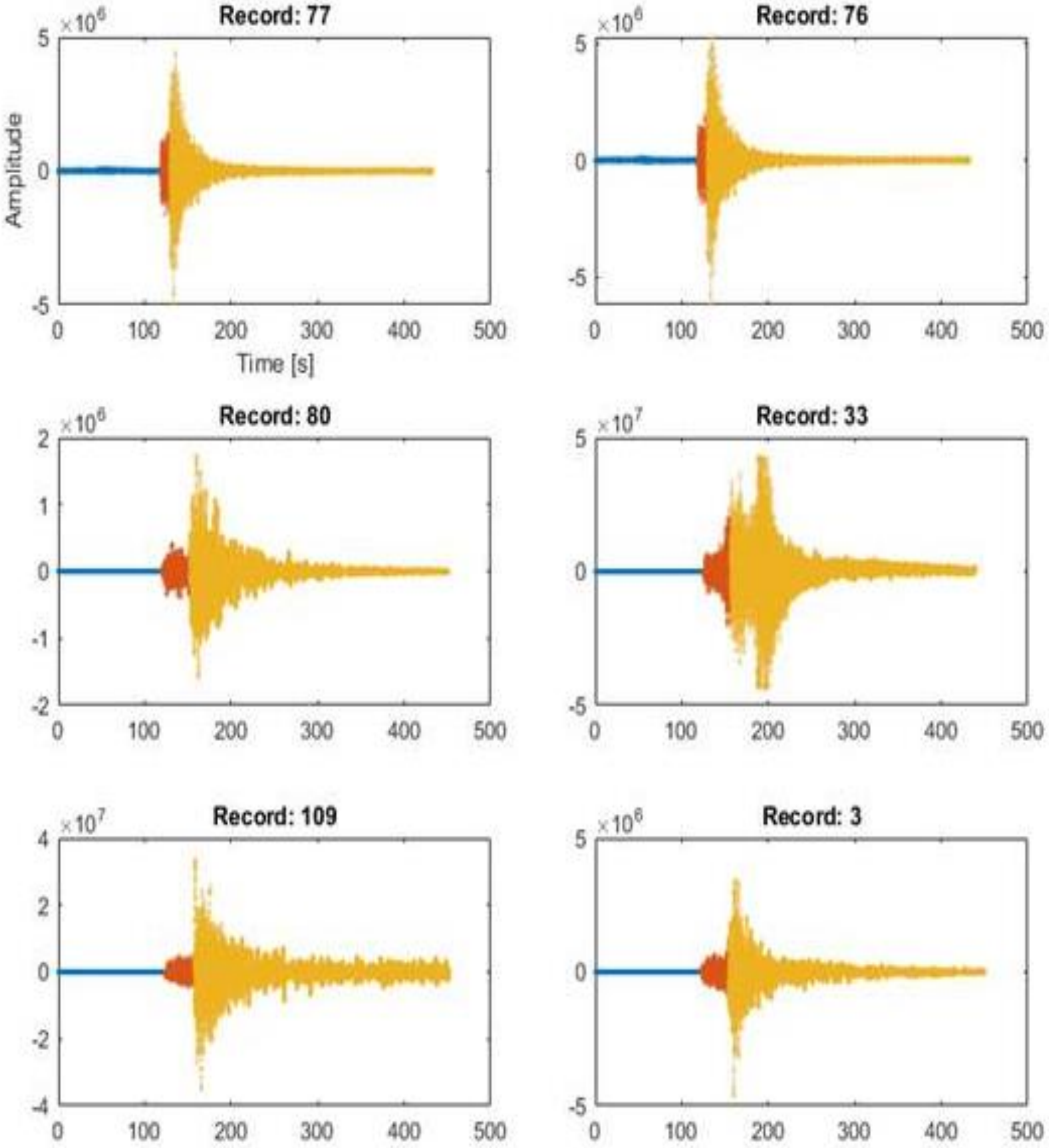




Generalization – NAM

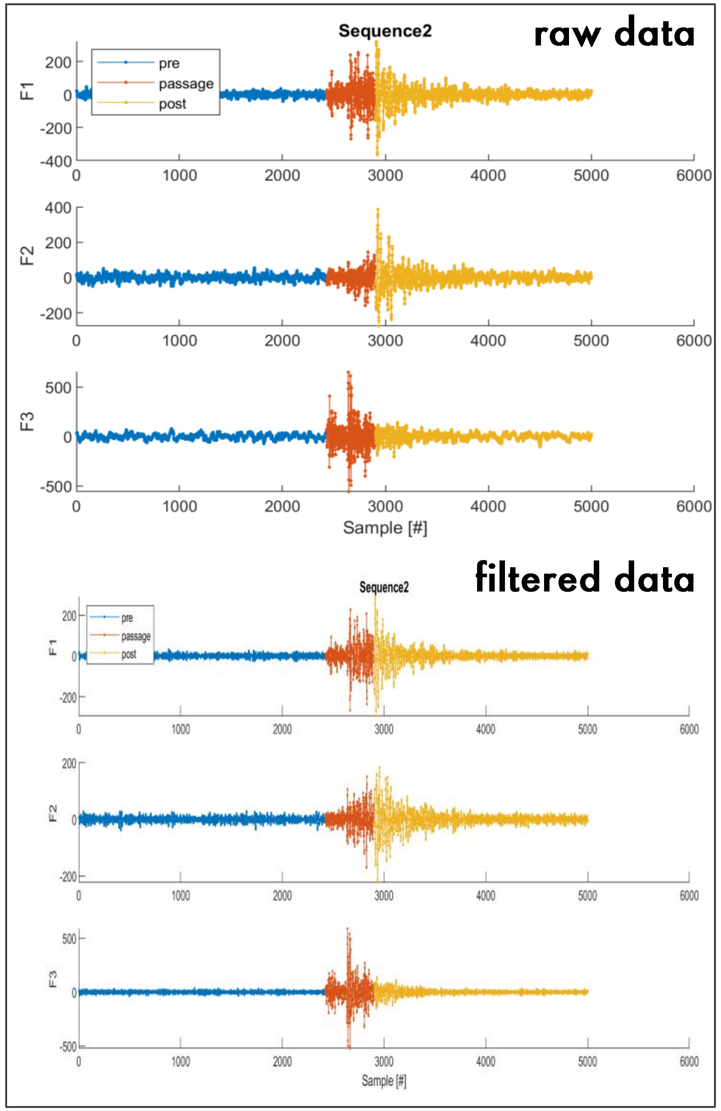
Can network trained on Albania earthquakes accurately detect “local” earthquakes from Netherlands?

What’s Different?

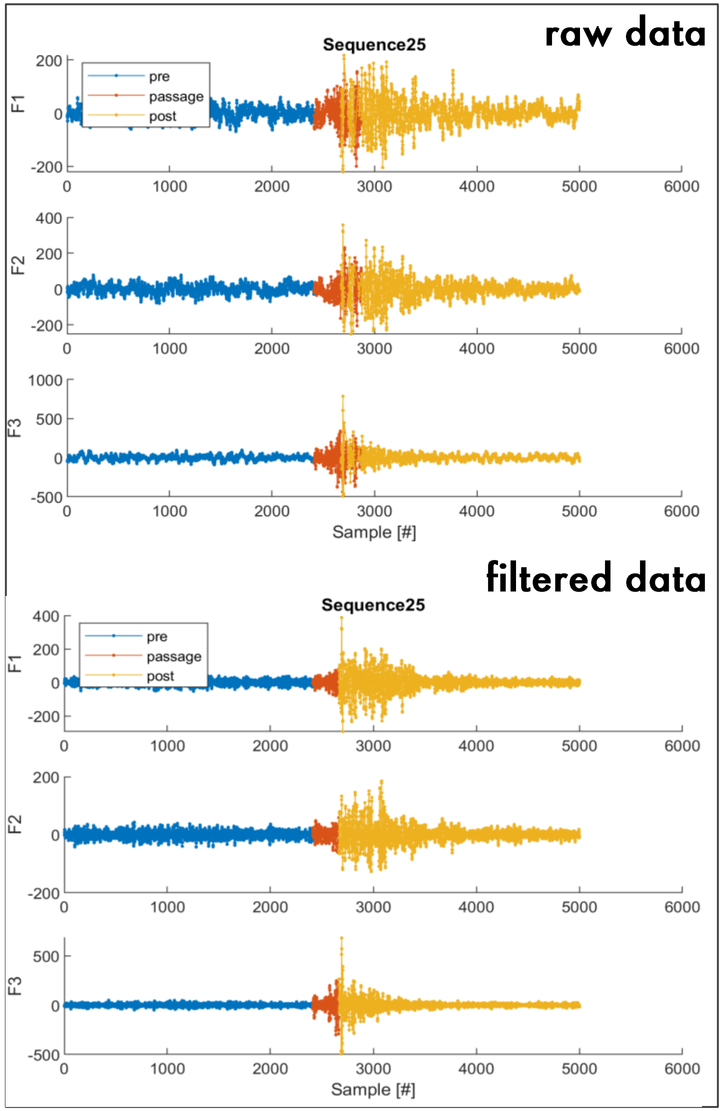
1. Mechanism
2. Geology
3. Instrumentation (downhole vs surface)
4. Level of anthropogenic noise
5. Picking of NAM earthquakes done on bandpass-filtered data

Authors wish to acknowledge and thank Shell NAM for providing the NL data and letting us present results at this meeting.

Earthquake #1



Earthquake #2

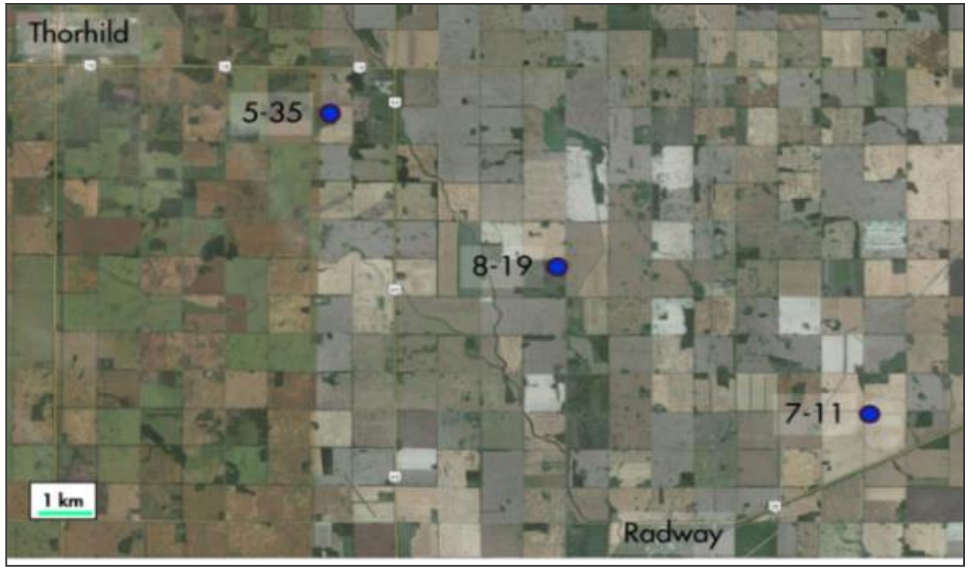


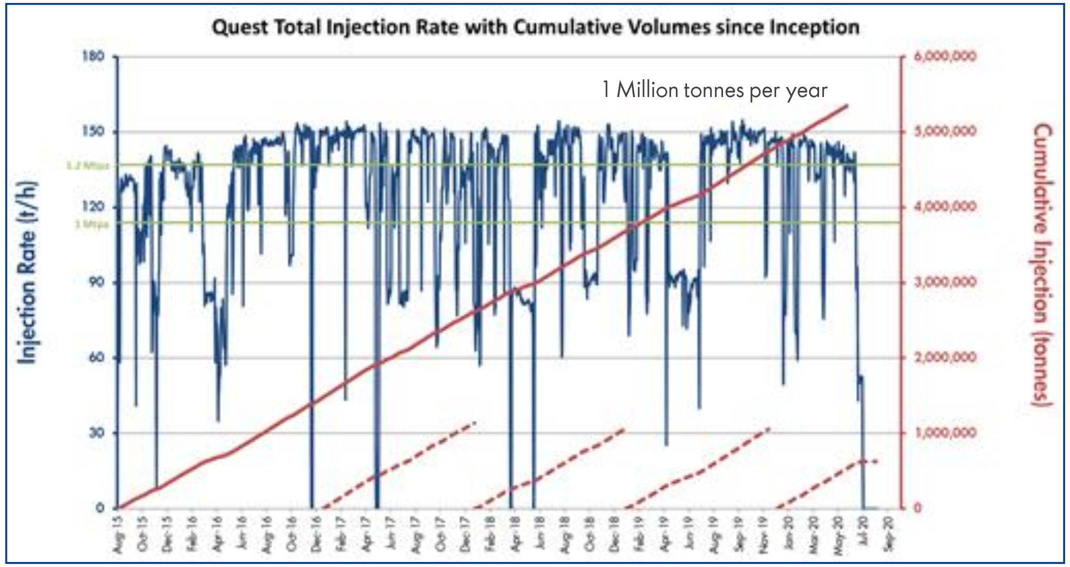
Generalization – Quest CCS

Can network trained on Albania earthquakes accurately detect "local" earthquakes at Quest CCS facility in Canada?

What's Different?

1. Mechanism
2. Geology (all EQ's in below reservoir)
3. Instrumentation (downhole vs surface)
4. Level of anthropogenic noise

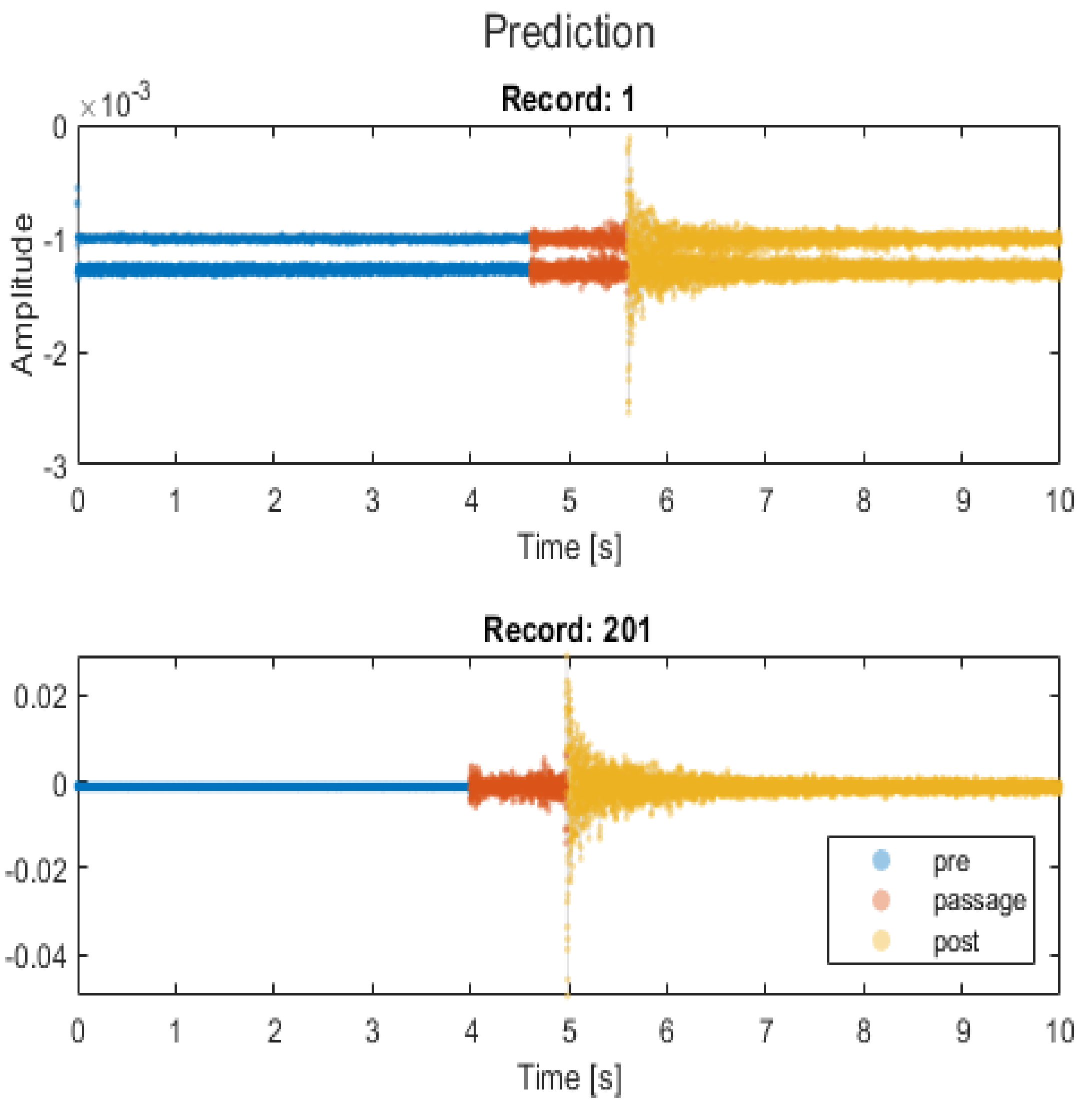


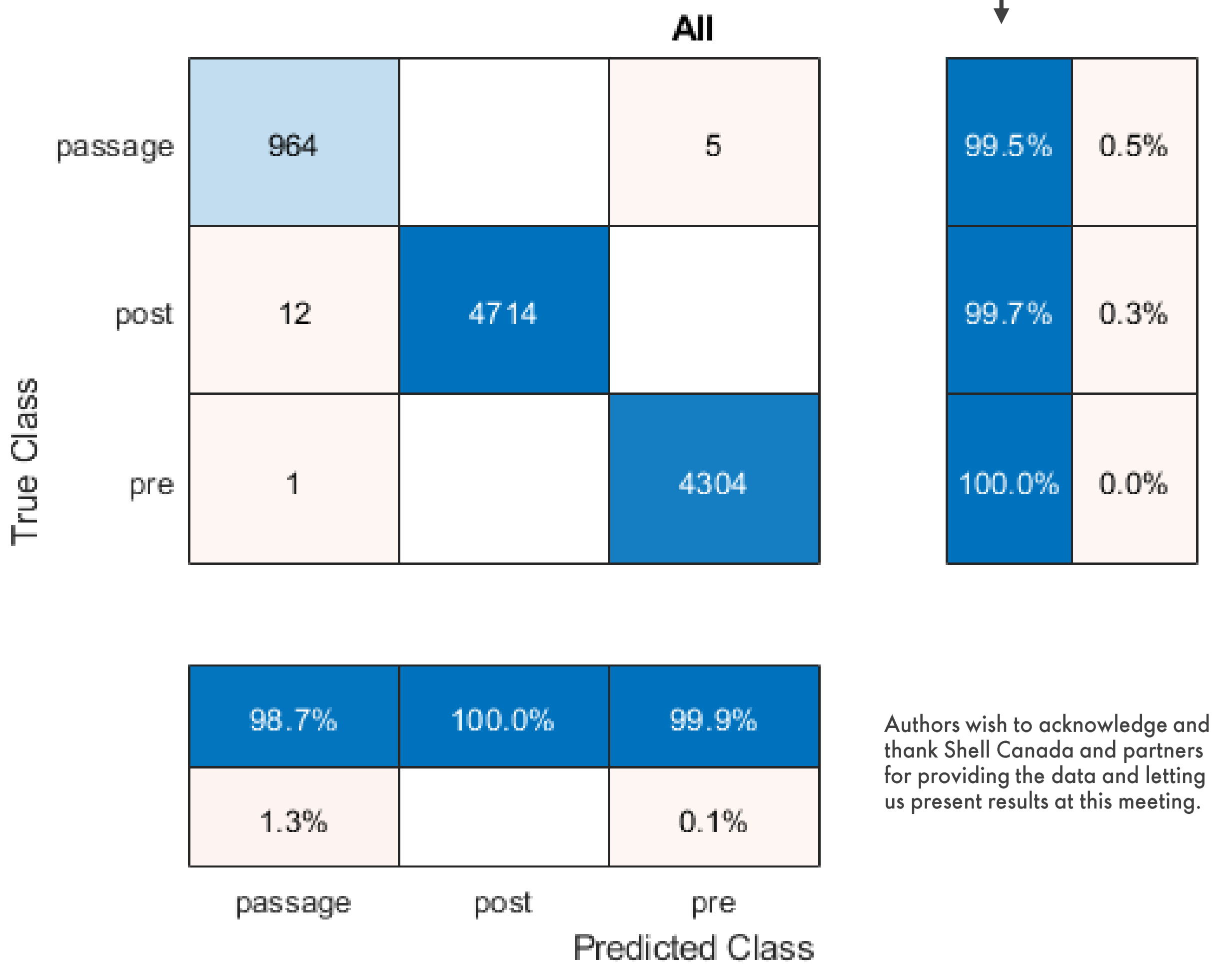


Figures provided by Quest

Generalization – Quest CCS

Excellent results but .....

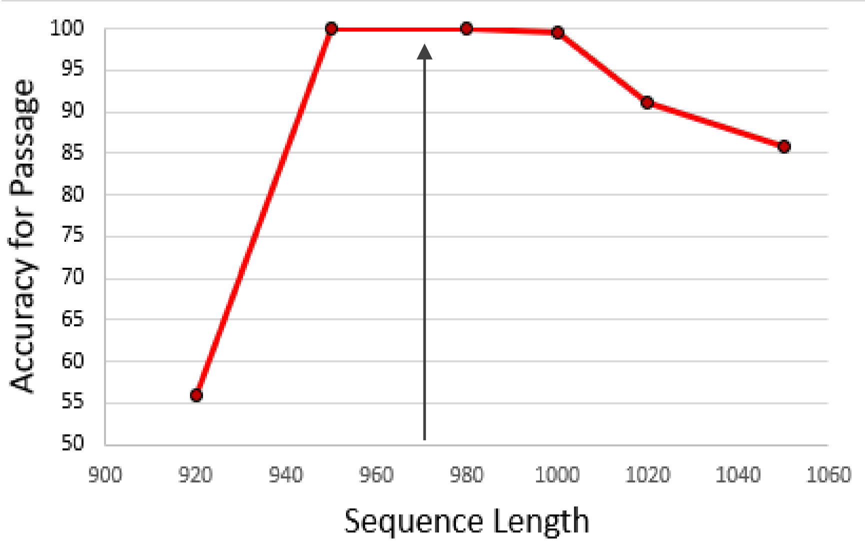


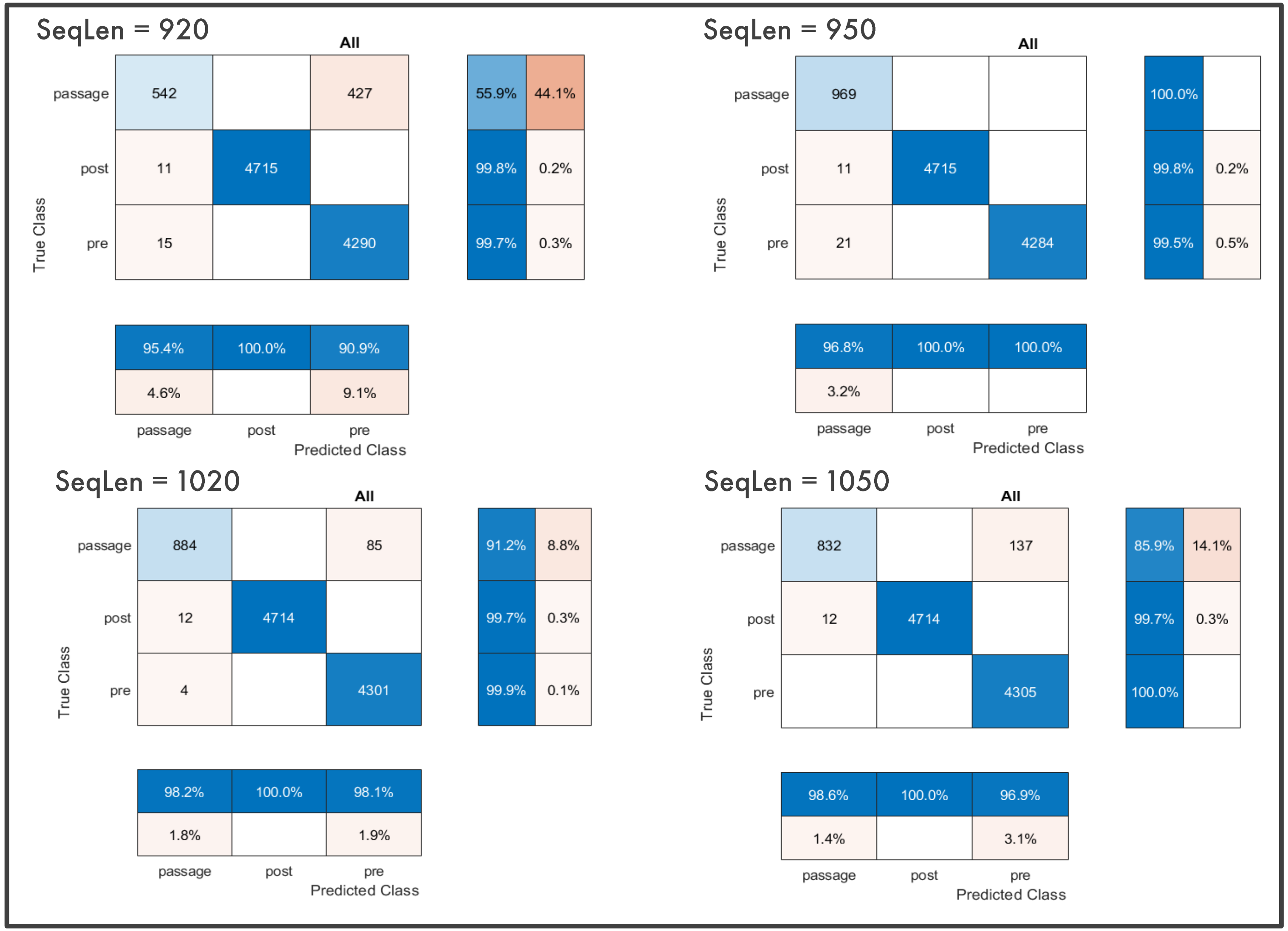


Authors wish to acknowledge and thank Shell Canada and partners for providing the data and letting us present results at this meeting.

Generalization – Quest CCS

- Accuracy depends VERY STRONGLY on sequence length fed into network.
- We trained Albania on 221 sequence length, but optimal SeqLen for Quest is ~970. Hard to predict in advance!
- Not yet figured out why.
- Might limit applications to new fields?





How much training data is needed?

less time
less money

less time
less money

1% of data

Train

True Class \ Predicted Class	passage	post	pre		
passage	63760	1245	736	97.0%	3.0%
post	8318	148935	31025	79.1%	20.9%
pre	5443	13548	158355	89.3%	10.7%
	82.2%	91.0%	83.3%		
	17.8%	9.0%	16.7%		

Test

True Class \ Predicted Class	passage	post	pre		
passage	2544662	101687	32585	95.0%	5.0%
post	532138	6252439	1513356	75.3%	24.7%
pre	229148	583954	6578678	89.0%	11.0%
	77.0%	90.1%	81.0%		
	23.0%	9.9%	19.0%		

77%

5% of data

Train

True Class \ Predicted Class	passage	post	pre		
passage	315009	948	2443	98.9%	1.1%
post	1918	950048	2406	99.5%	0.5%
pre	6412	7	866381	99.3%	0.7%
	97.4%	99.9%	99.4%		
	2.6%	0.1%	0.6%		

Test

True Class \ Predicted Class	passage	post	pre		
passage	2606192	47522	25220	97.3%	2.7%
post	62826	8208370	26737	98.9%	1.1%
pre	87319	42806	7261655	98.2%	1.8%
	94.6%	98.9%	99.3%		
	5.4%	1.1%	0.7%		

95%

100% of data

Train

True Class \ Predicted Class	passage	post	pre		
passage	6214242	19278	36139	99.1%	0.9%
post	138789	19040151	122315	98.6%	1.4%
pre	75993	13	17215757	99.6%	0.4%
	96.7%	99.9%	99.1%		
	3.3%	0.1%	0.9%		

Test

True Class \ Predicted Class	passage	post	pre		
passage	2649105	11563	18266	98.9%	1.1%
post	85487	8152462	59984	98.2%	1.8%
pre	35691	19	7356070	99.5%	0.5%
	95.6%	99.9%	98.9%		
	4.4%	0.1%	1.1%		

96%

Thank you

Questions?