

# Layer-finding in Radar Echograms using Probabilistic Graphical Models



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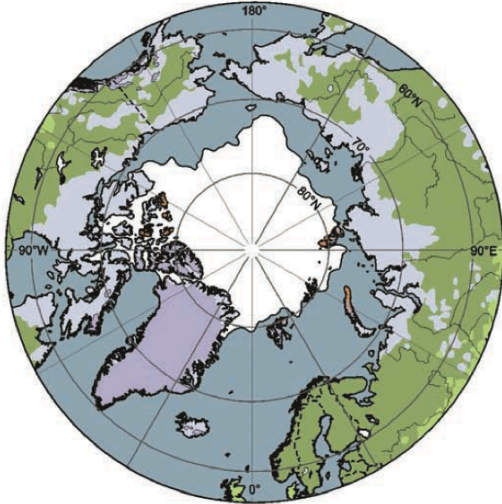


**John D. Paden**

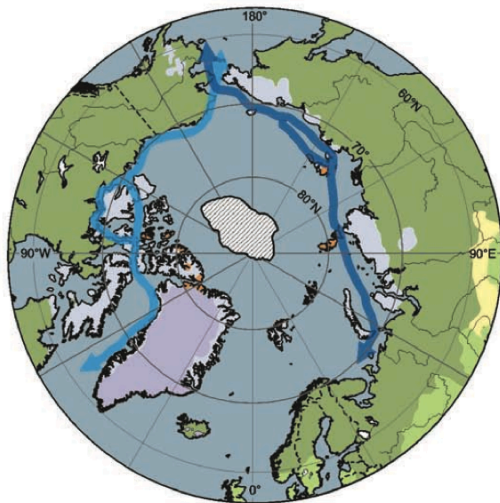
Center for Remote Sensing of Ice Sheets  
University of Kansas, USA

# Ice and climate

Current conditions



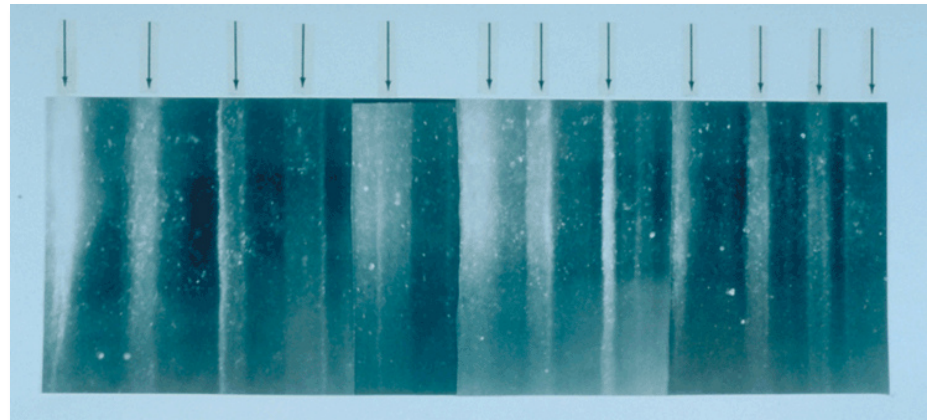
Projected conditions, 2085



[IPCC 2007]



U.S. Antarctica Program



U.S. NOAA

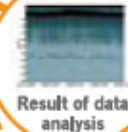


**CReSIS**  
Center for Remote  
Sensing of Ice Sheets

Iridium, Inmarsat, VSAT  
3Kbps - 1.5Mbps (monitoring)



Greenland  
Polar Grid Project Site



Result of data  
analysis



Polar Grid L48 160+64  
IBM BladeCenter® Servers  
with in-depth processing  
located at IU and ECSU



BladeCenter® S  
chassis with 12  
hot-swappable SATA  
drive slots

Base Camp  
with a storage and  
compute cluster



Twin Otter or P-3  
airplane used for wide  
area SAR survey and  
aerial radar



Mobile Sensors  
transmit data  
to Base Camp



Mobile Field Station  
(snow-modified SUV pulling  
a server-equipped sled)



Radar sled under  
construction at  
CReSIS in preparation  
for 2008 Greenland  
expedition.

● TeraGrid Sites

● Center for the Remote Sensing  
of Ice Sheets (CReSIS)



Polar Grid laboratory at ECSU  
supports CI training and distance  
education. Mac workstations run  
Condor, allowing student  
interaction with data analysis.

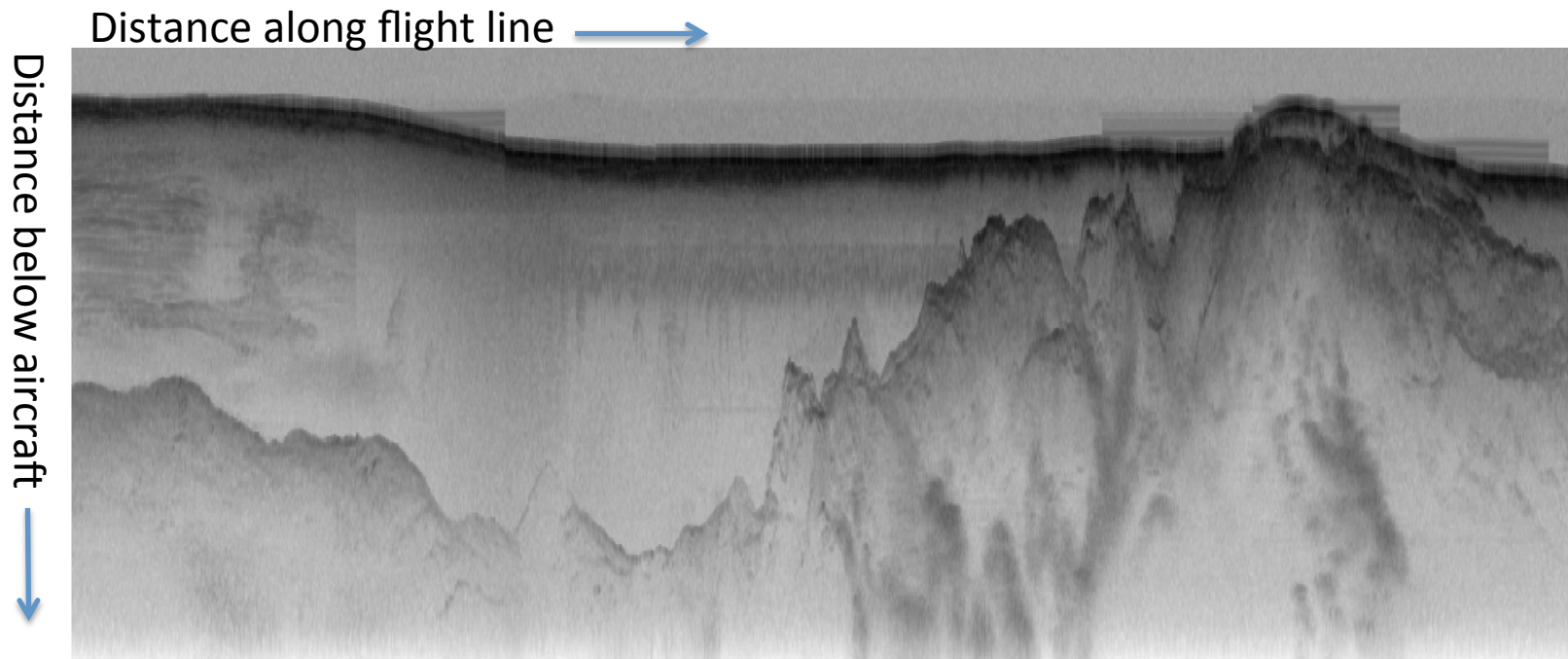
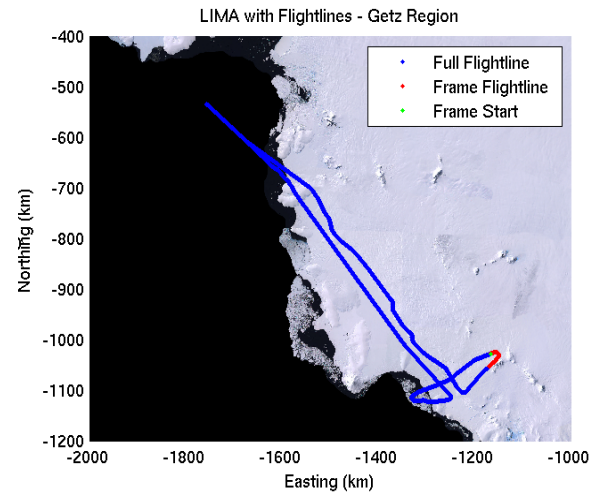
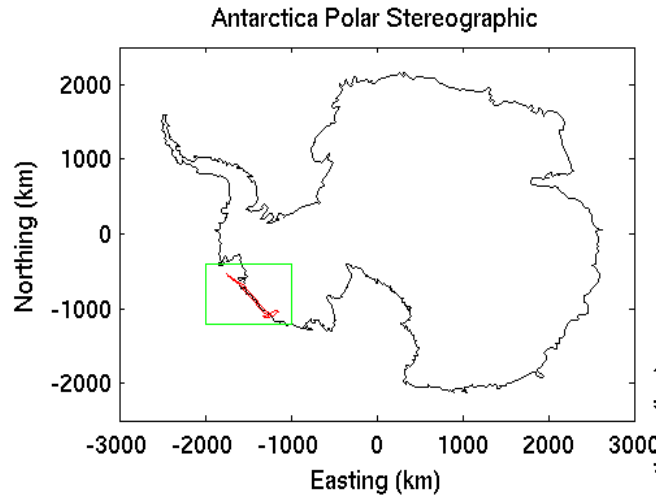


CNS-0723054

Thwaites Glacier, Antarctica:  
Polar Grid Project Site

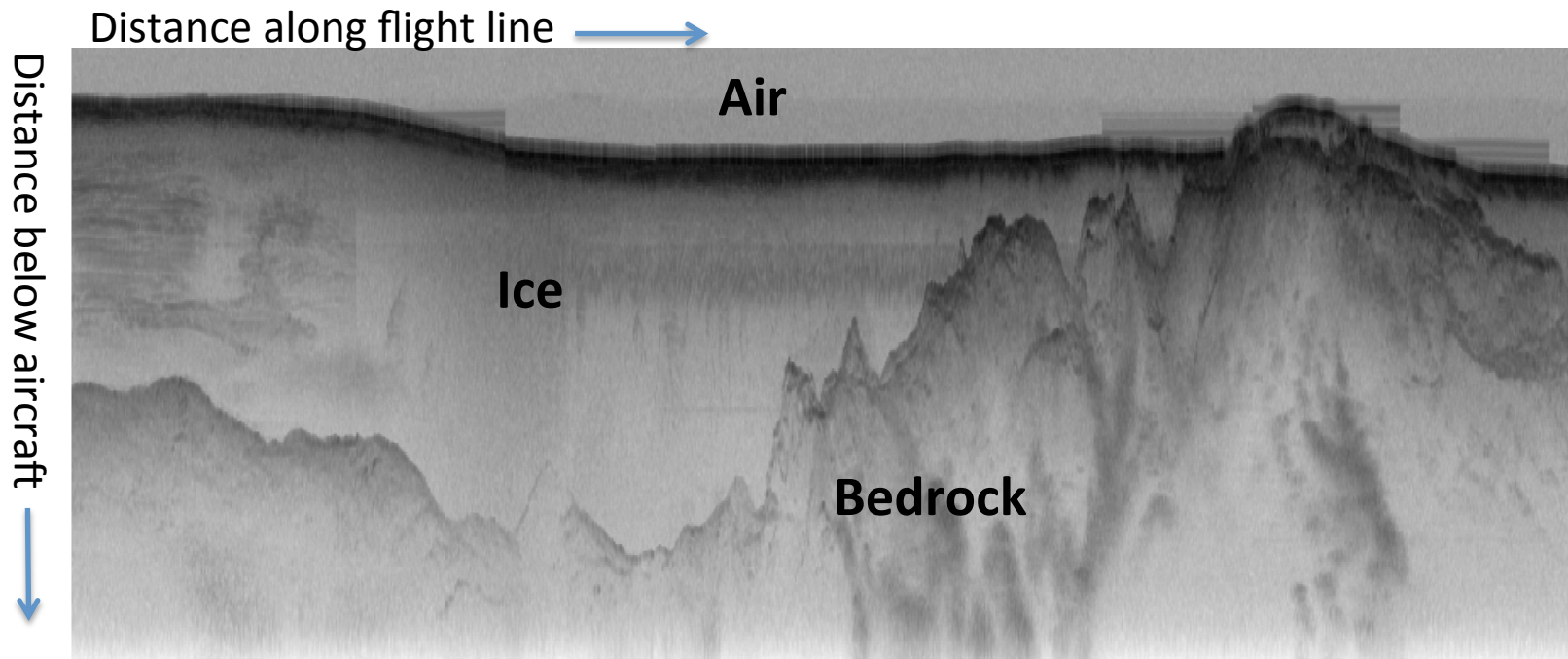
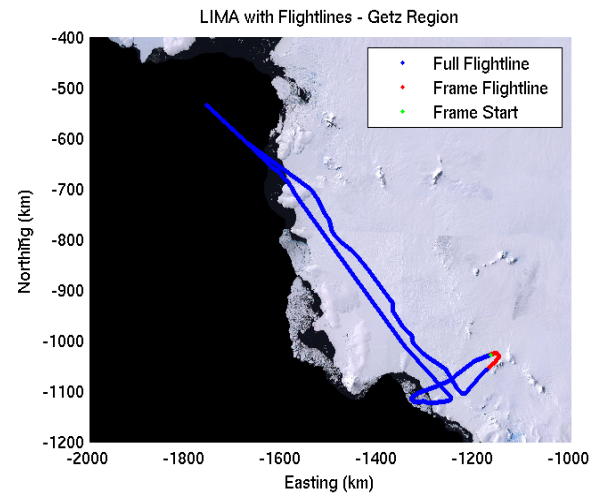
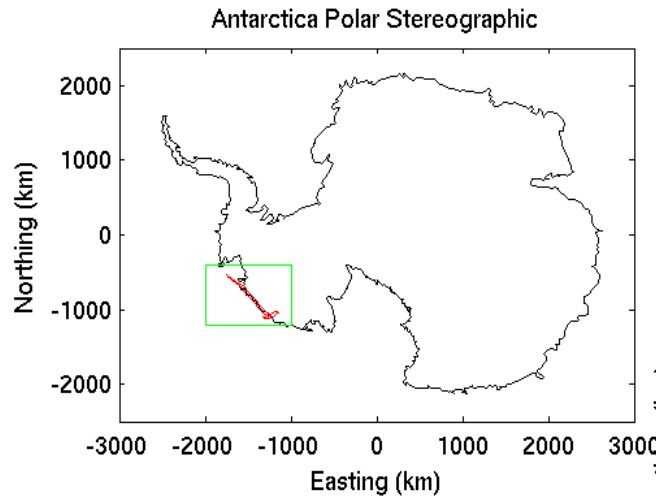


# Ice sheet radar echograms

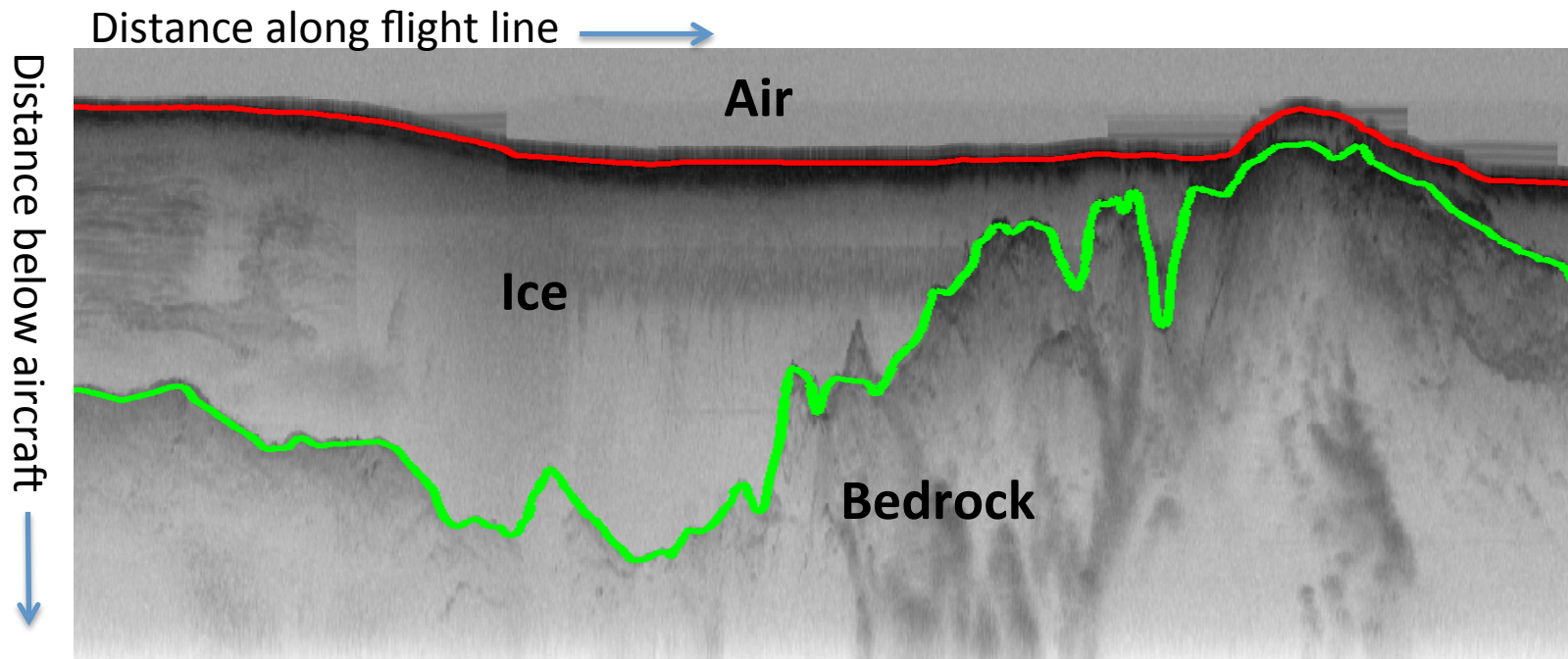
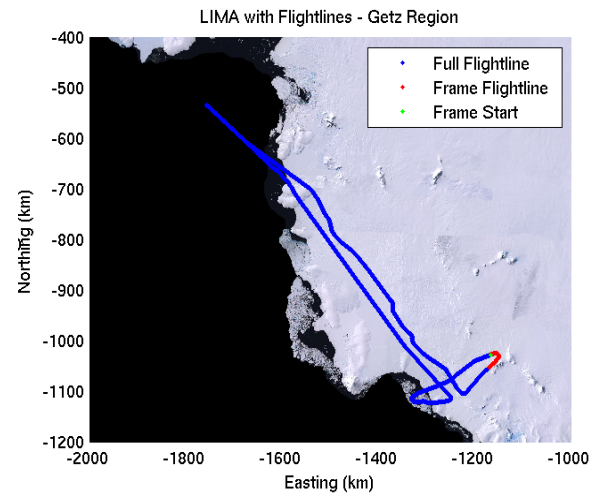
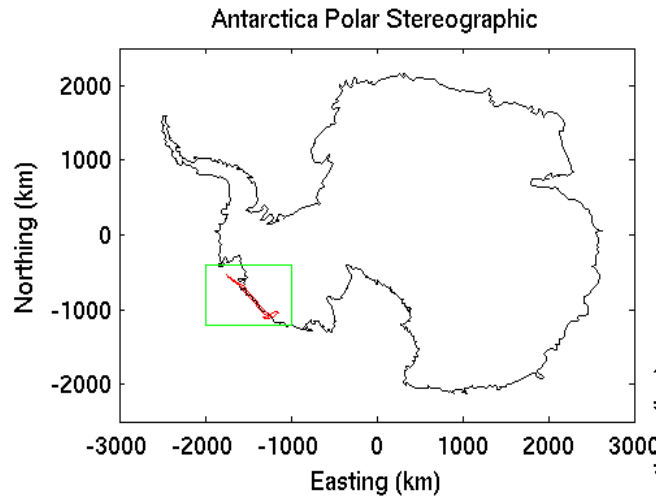




# Ice sheet radar echograms



# Ice sheet radar echograms



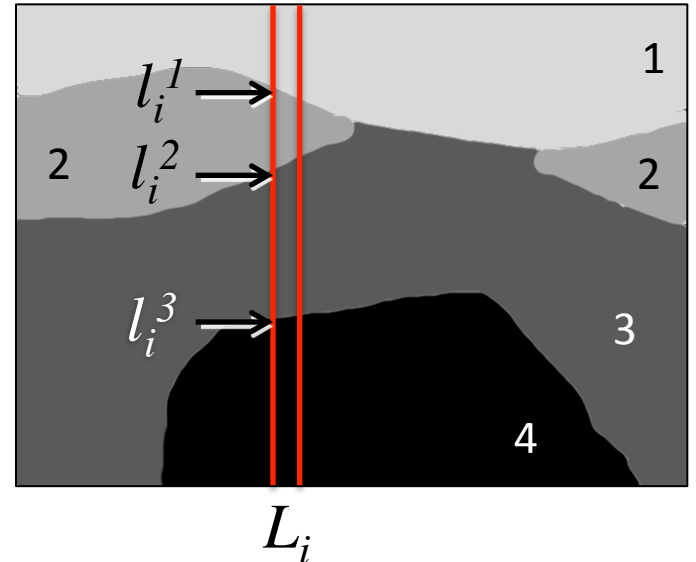
# Related work

- General-purpose image segmentation
  - [Haralick1985], [Kass1998], [Shi2000], [Felzenszwalb2004], ...
- Subsurface imaging
  - [Turk2011], [Allen2012], ...
- Buried object detection
  - [Trucco1999], [Gader2001], [Frigui2005], ...
- Layer finding in ground-penetrating echograms
  - [Freeman2010], [Ferro2011], ...



# Tiered segmentation

- Layer-finding is a *tiered segmentation problem* [Felzenszwalb2010]
  - Label each pixel with one of  $[1, K+1]$ , under the constraint that if  $y < y'$ , label of  $(x, y) \leq$  label of  $(x, y')$



- Equivalently, find  $K$  boundaries in each column
  - Let  $L_i = (l_i^1, \dots, l_i^K)$  denote the row indices of the  $K$  region boundaries in column  $i$
  - Goal is to find labeling of whole image,  $L = (L_1, \dots, L_n)$

# Probabilistic formulation

- Goal is to find most-likely labeling given image  $I$ ,

$$L^* = \arg \max_L P(L|I) = \arg \max_L P(I|L)P(L)$$

**Likelihood term** models  
how well labeling  
agrees with image

**Prior term** models how  
well labeling agrees with  
typical ice layer properties

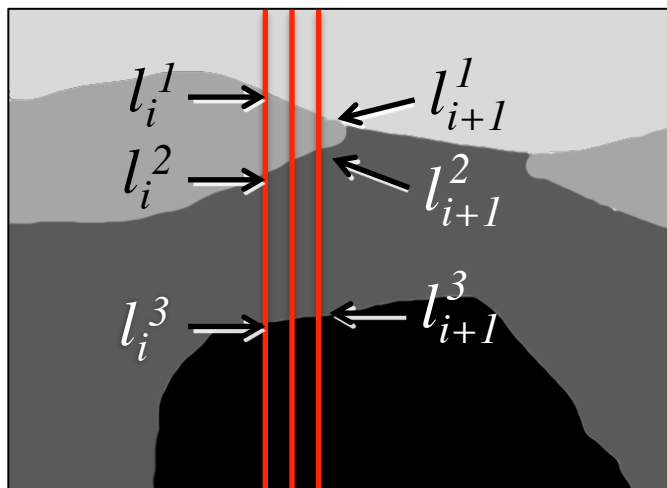
# Prior term

- Prior encourages smooth, non-crossing boundaries

$$P(L) \propto \prod_{i \in [2, n]} \prod_{k \in [1, K]} P(l_i^k - l_{i-1}^k | \sigma_k) P(l_i^k | l_i^{k-1})$$

**Zero-mean Gaussian** penalizes discontinuities in layer boundaries across columns

**Repulsive term** prevents boundary crossings; is 0 if  $l_i^k < l_i^{k-1}$  and uniform otherwise





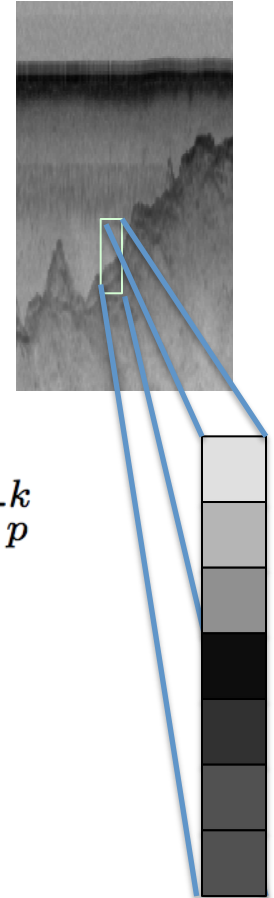
# Likelihood term

- Likelihood term encourages labels to coincide with layer boundary features (e.g. edges)

$$P(I|L) = \prod_{i \in [1, n]} P(I_i | L_i)$$

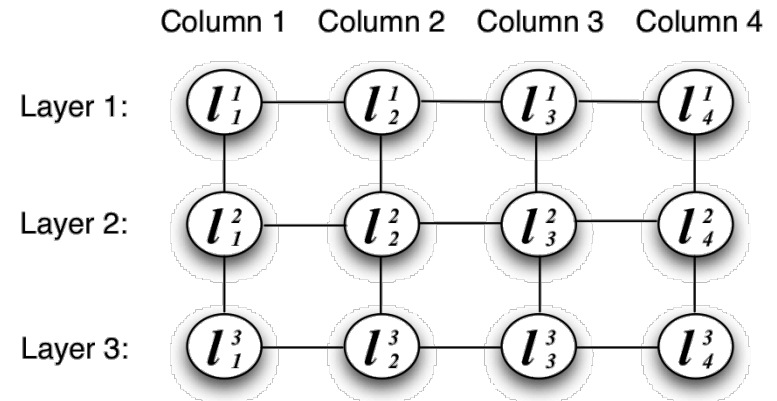
- Learn a single-column appearance template  $T_k$  consisting of Gaussians at each position  $p$ , with  $\mu_p^k, \sigma_p^k$
- Also learn a simple background model, with  $\mu_0, \sigma_0$
- Then likelihood for each column is,

$$P(I_i | L_i) = \prod_{p \in I_i} P(I(p) | \mu_0, \sigma_0) \prod_{k \in [1, K]} \prod_{p \in T_k} \frac{P(I(p + l_i^k) | \mu_p^k, \sigma_p^k)}{P(I(p + l_i^k) | \mu_0, \sigma_0)}$$



# Efficient inference

- Finding  $L$  that maximizes  $P(L / I)$  involves inference on a Markov Random Field



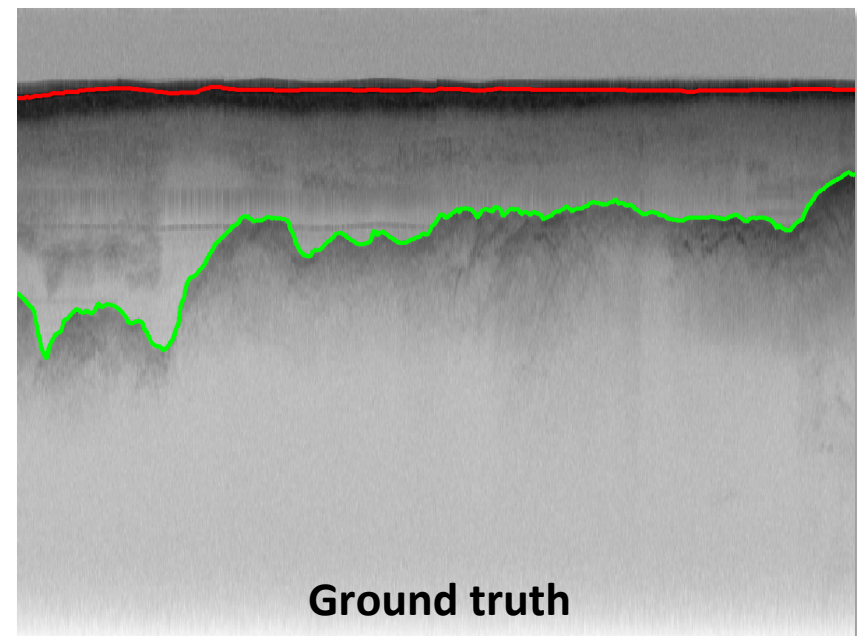
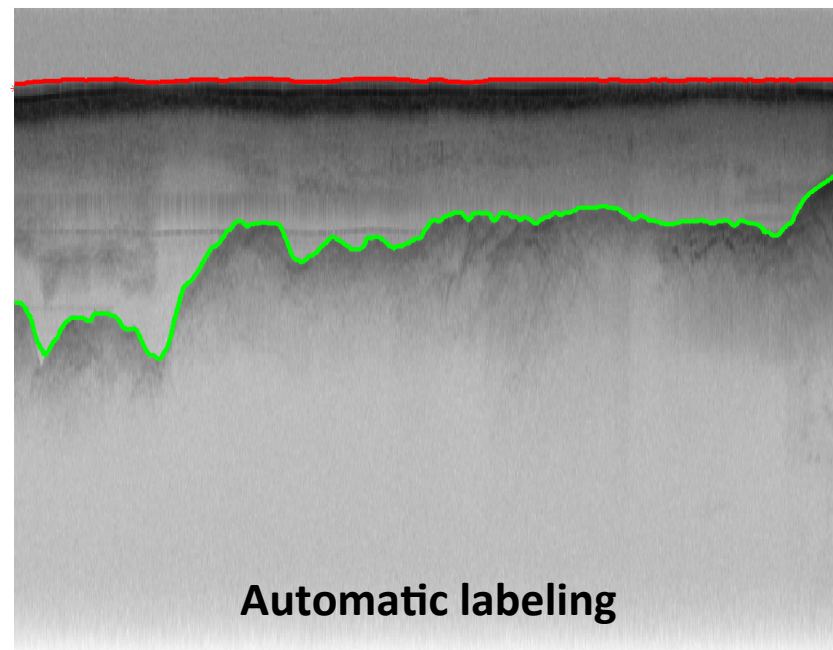
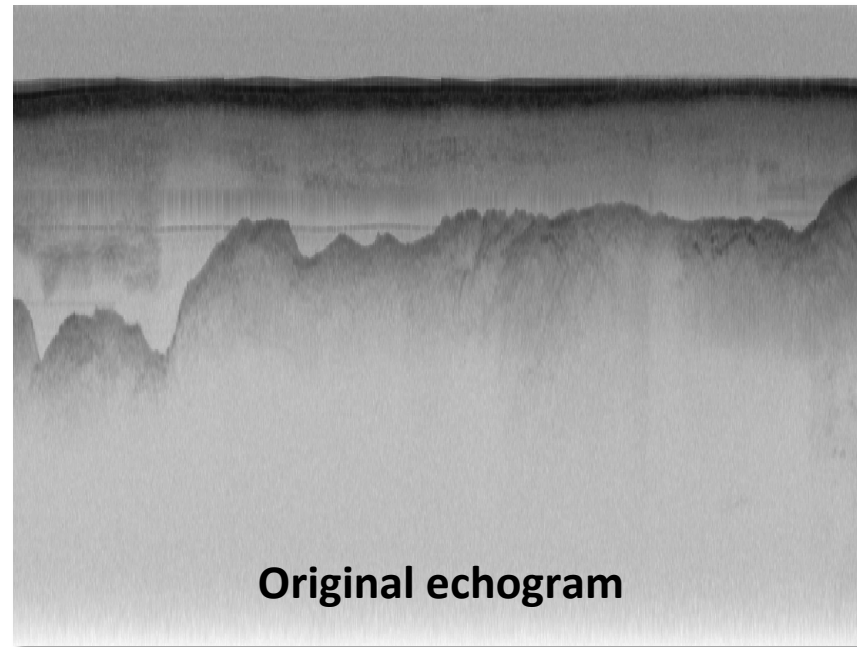
- Simplify problem by solving each row of MRF in succession, using the Viterbi algorithm
- Naïve Viterbi requires  $O(Kmn^2)$  time, for  $m \times n$  echogram with  $K$  layer boundaries
- Can use min-convolutions to speed up Viterbi (because of the Gaussian prior), reducing time to  $O(Kmn)$  [Crandall2008]

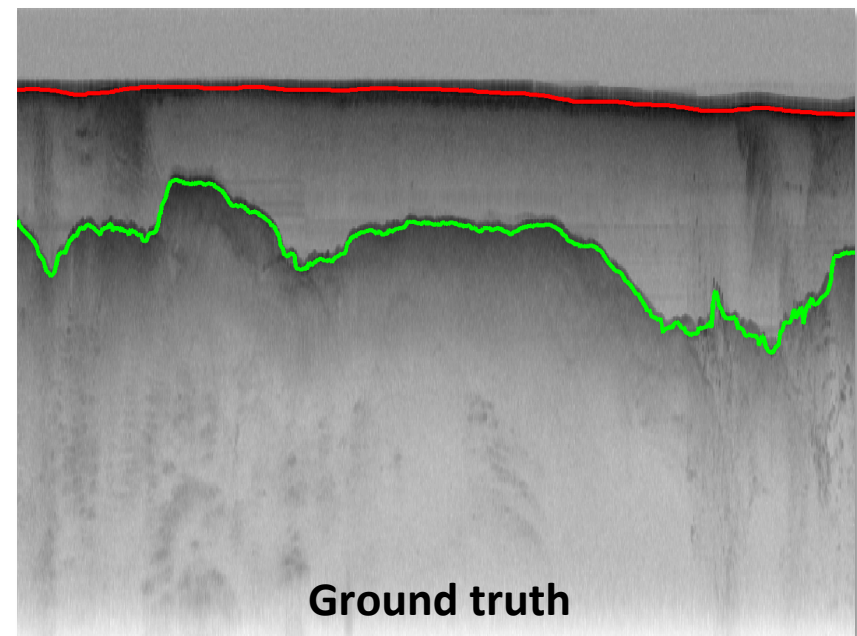
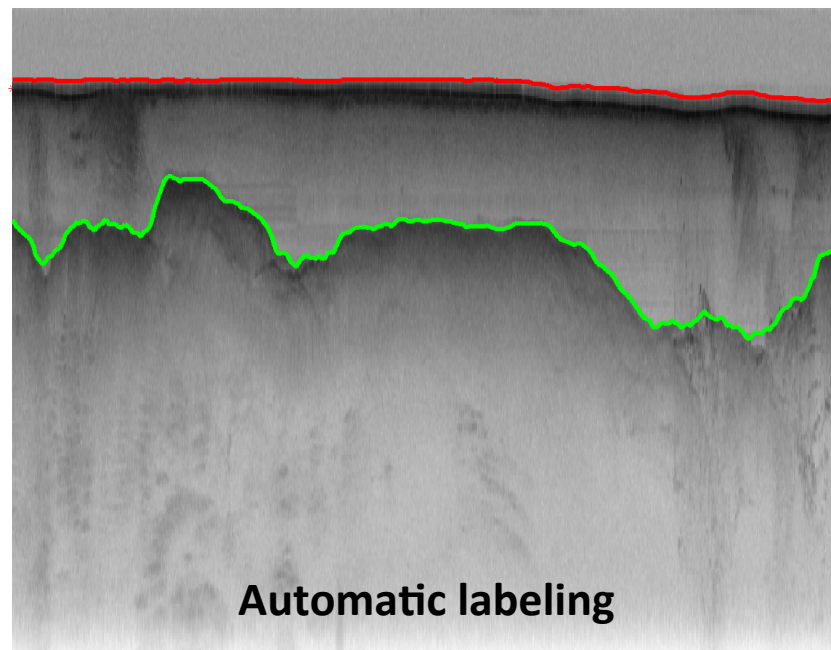
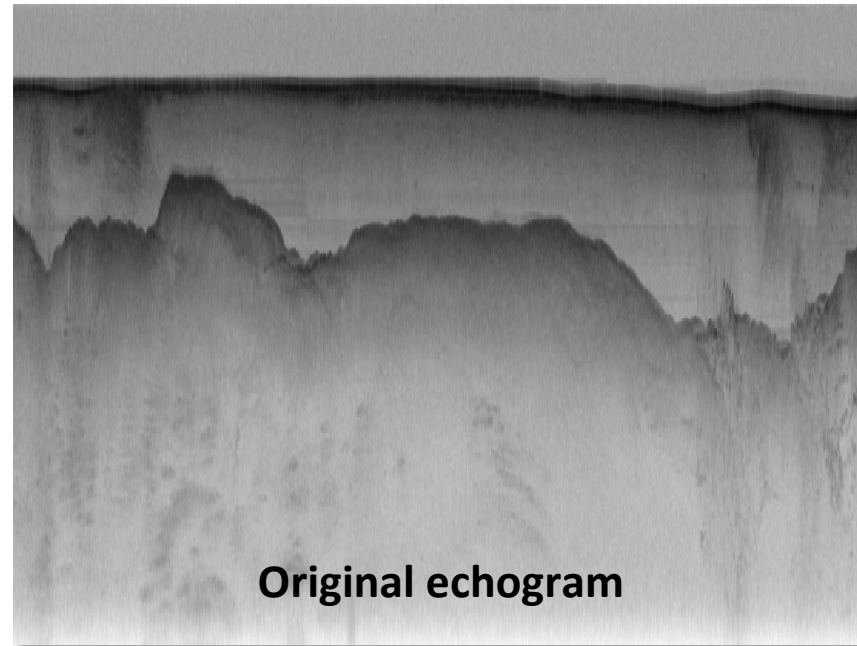
# Experimental results

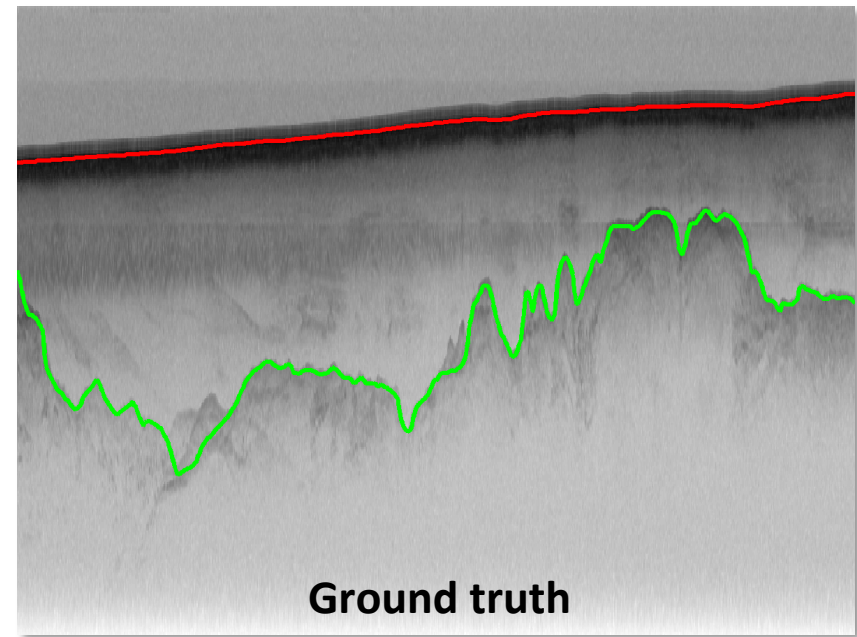
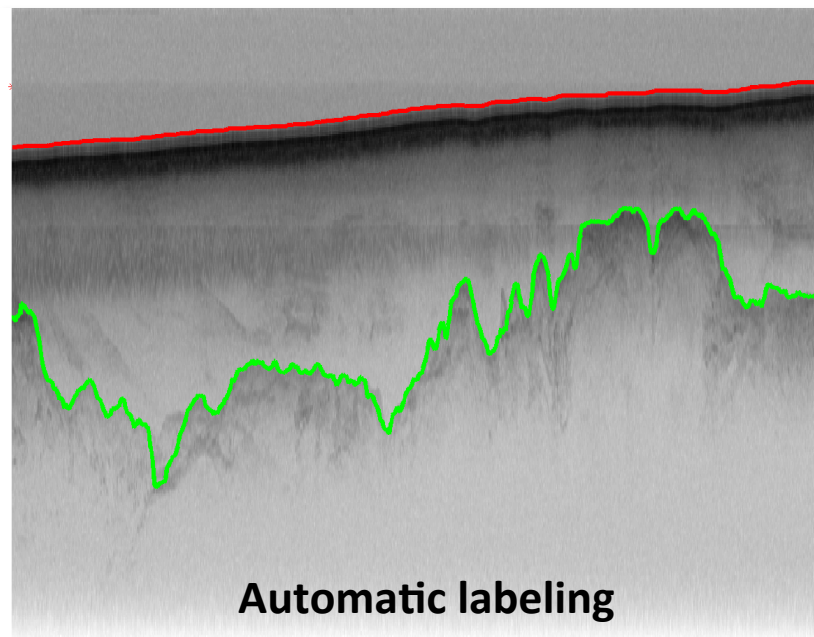
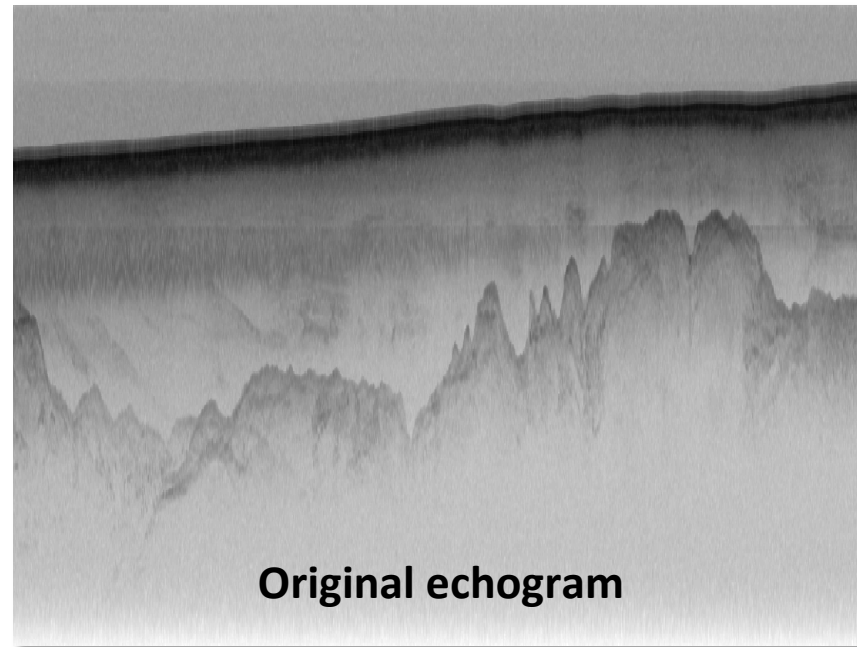
- Tested with 827 echograms from Antarctica
  - From Multichannel Coherent Radar Depth Sounder system in 2009 NASA Operation Ice Bridge [Allen12]
  - About 24,810 km of flight data
  - Split into equal-size training and test datasets



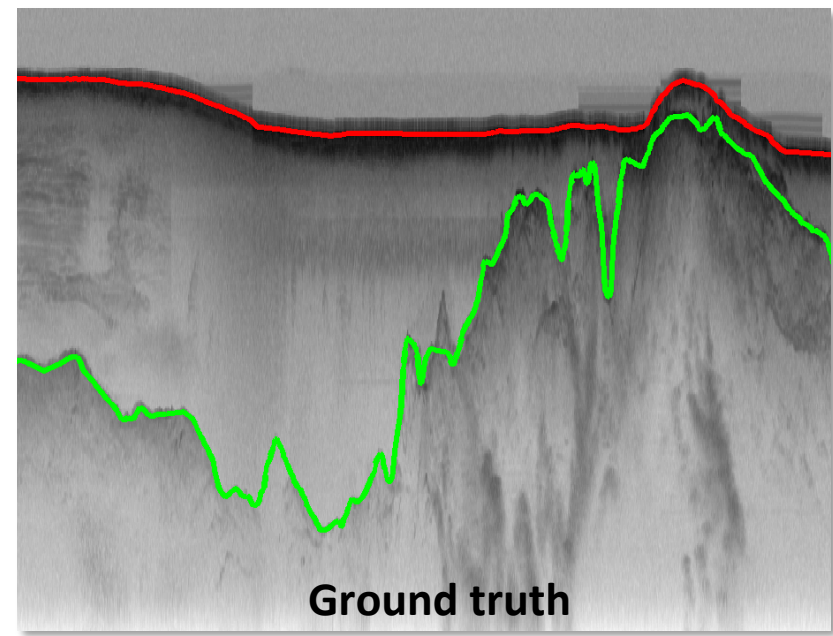
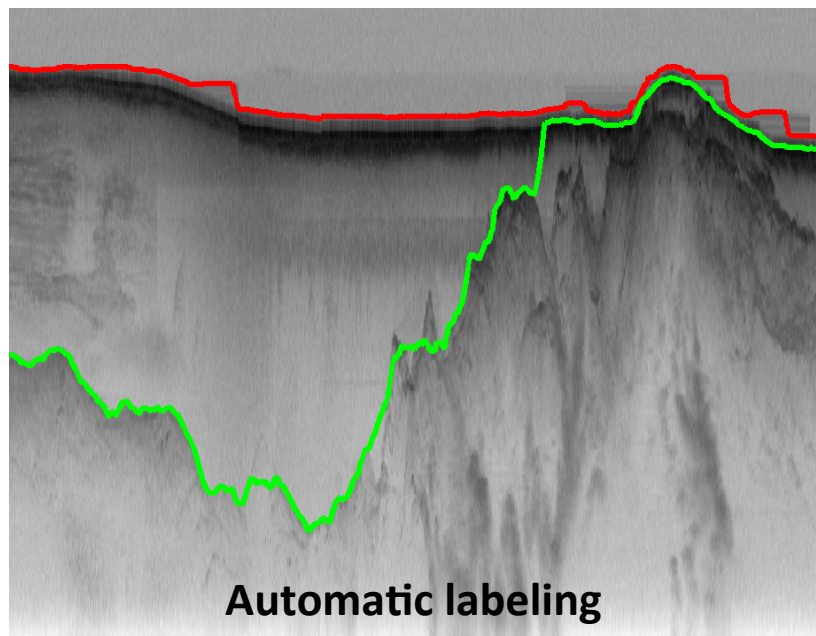
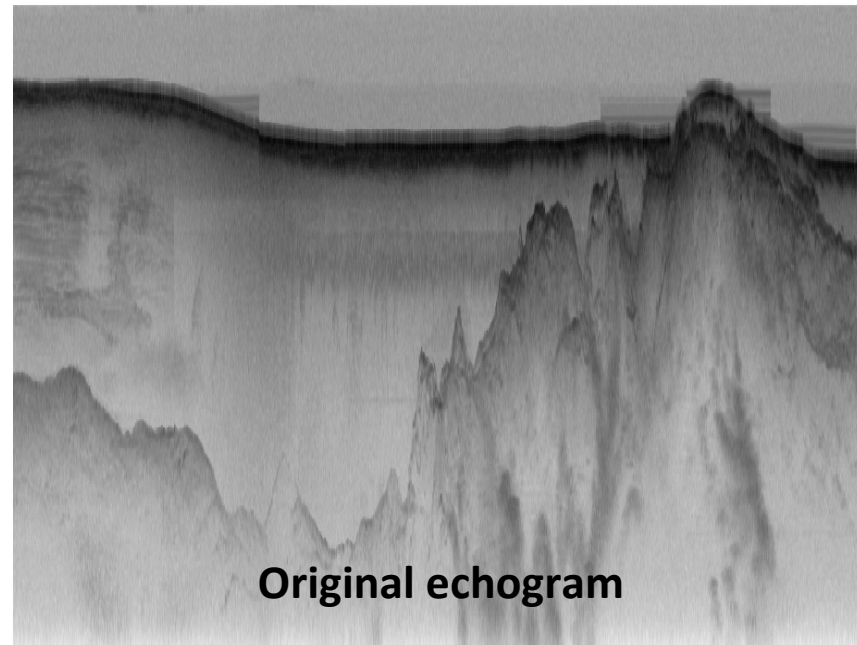




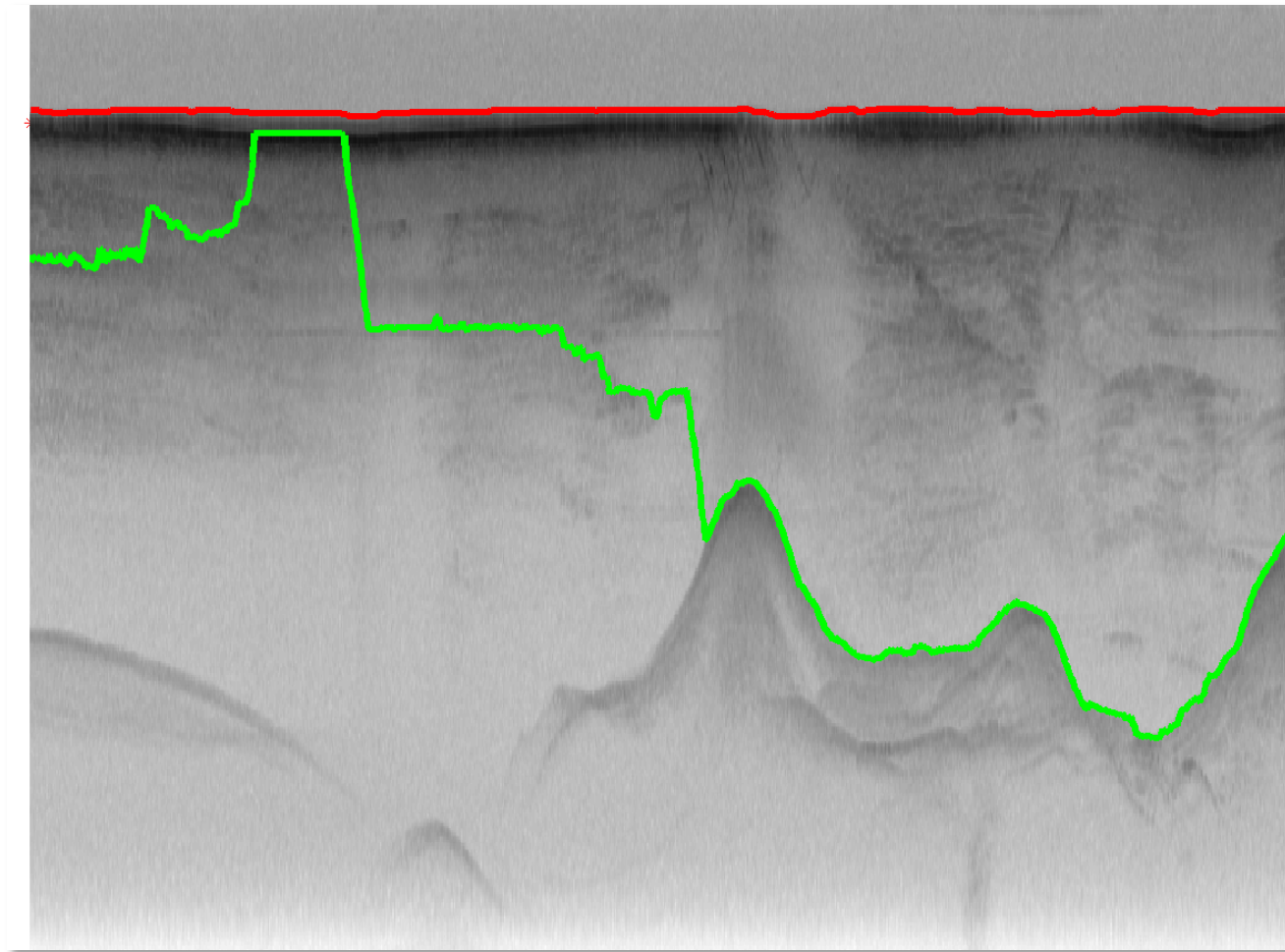




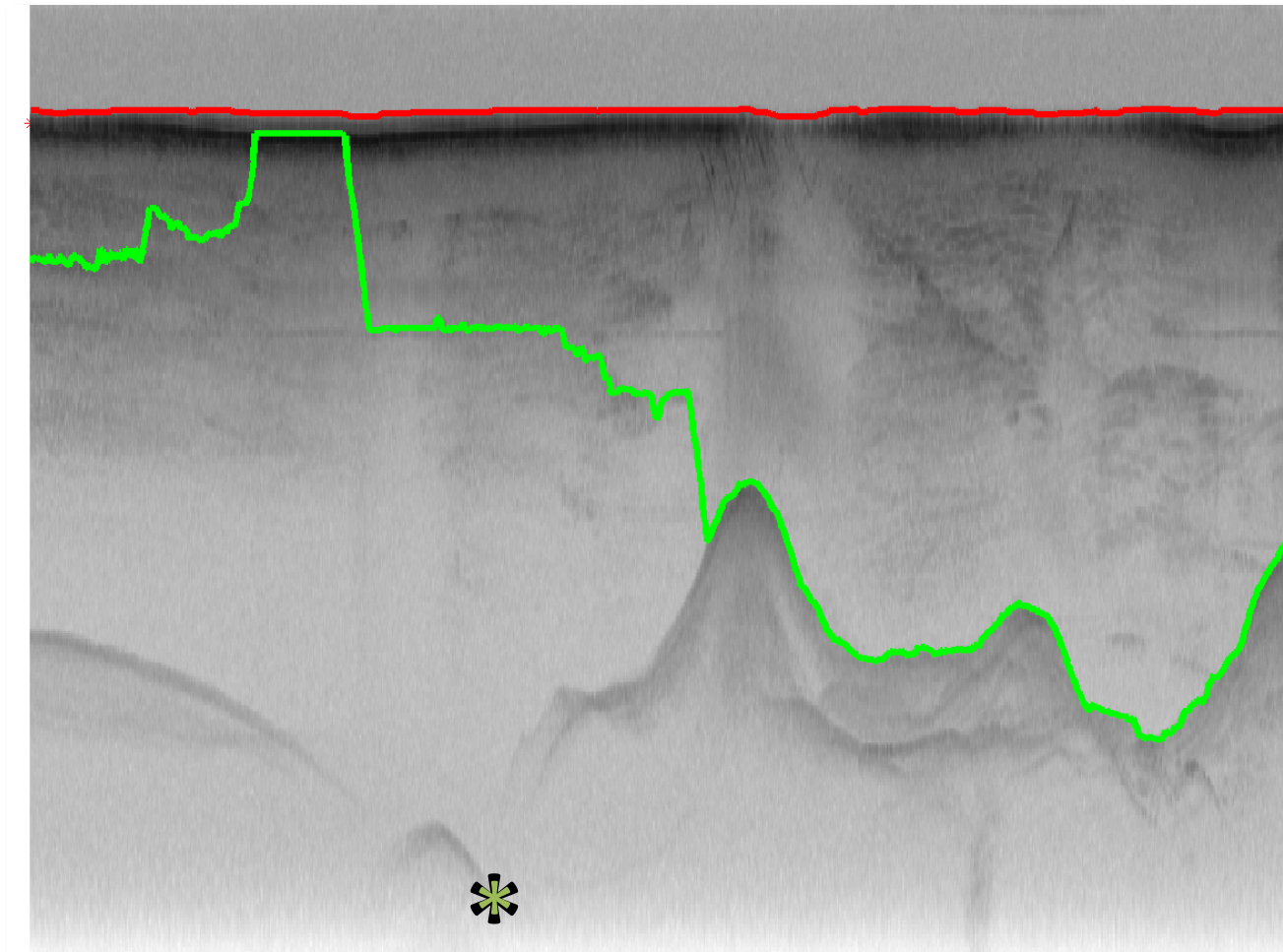




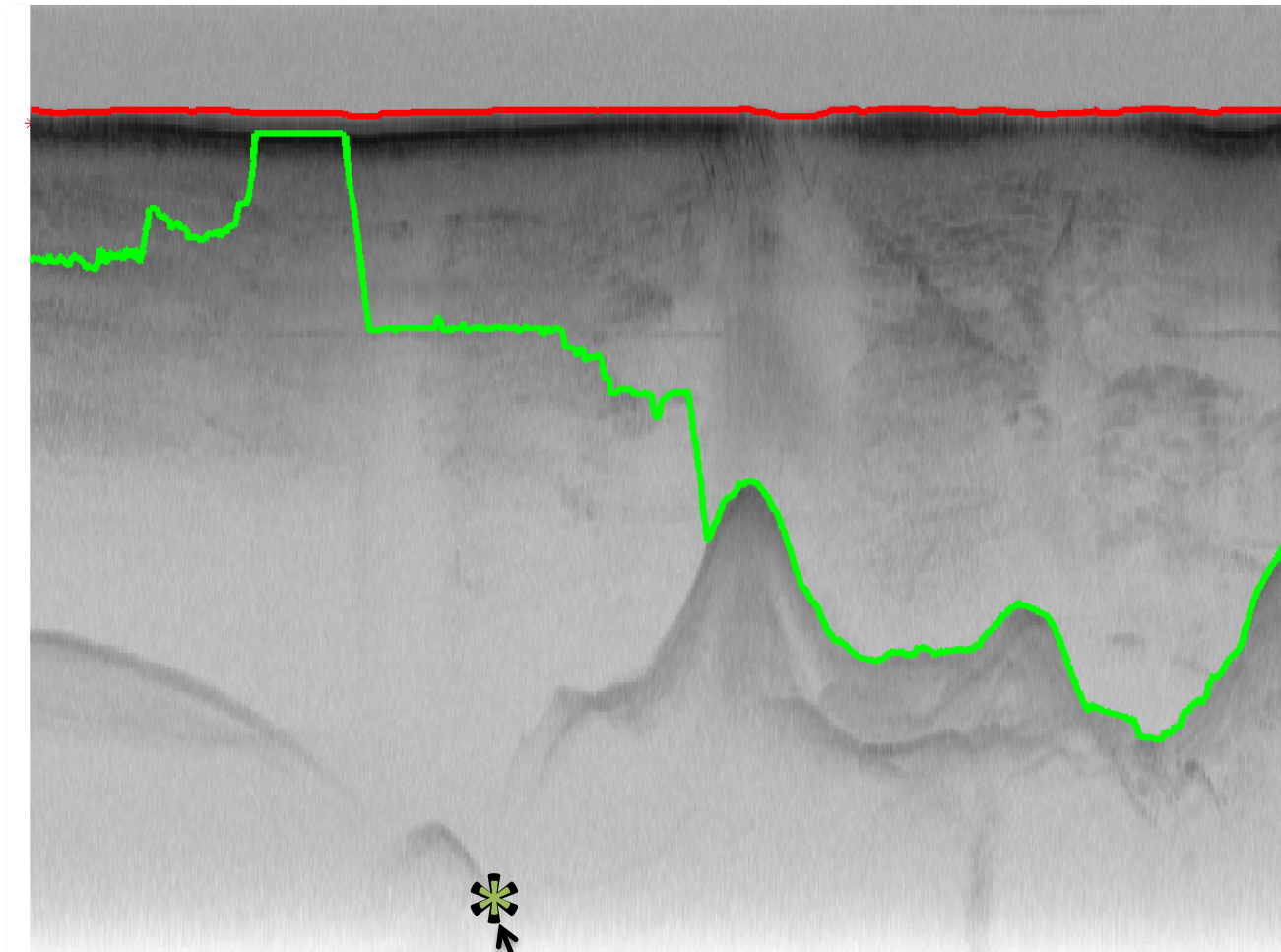
# User interaction



# User interaction

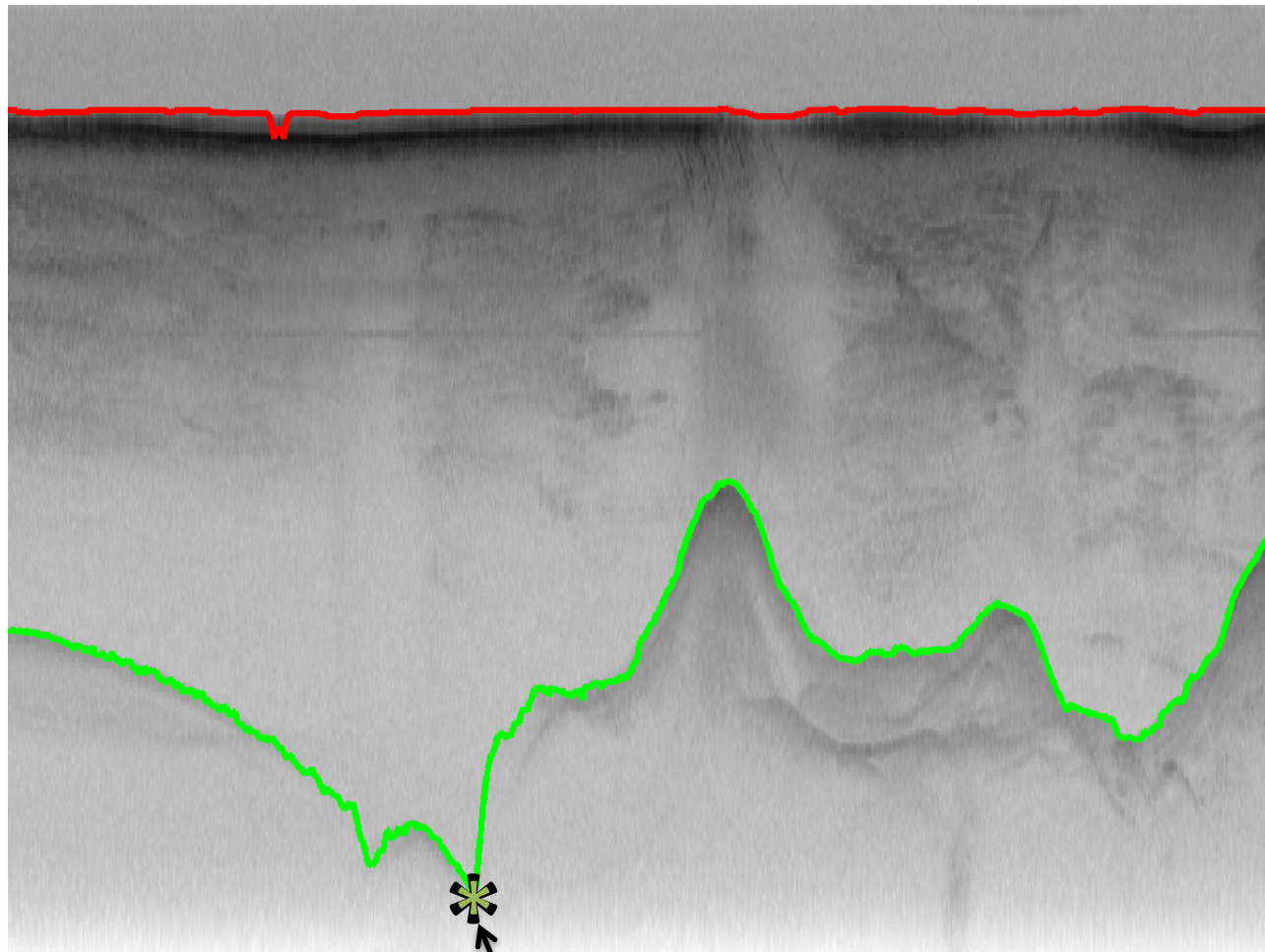


# User interaction



Modify  $P(L)$  such that this label has probability 1

# User interaction

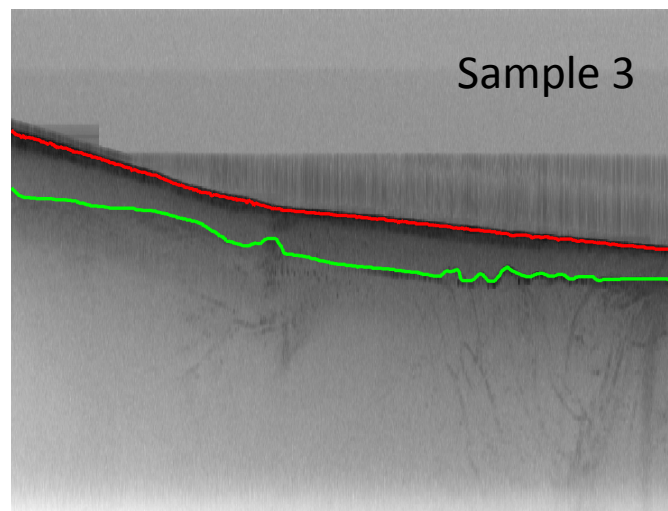
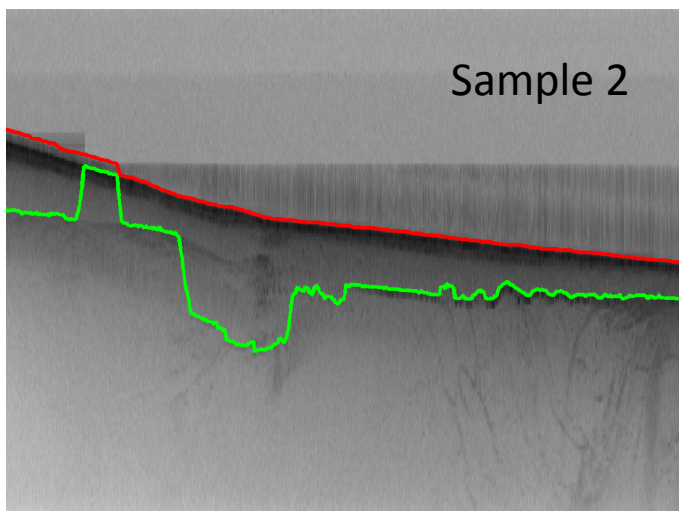
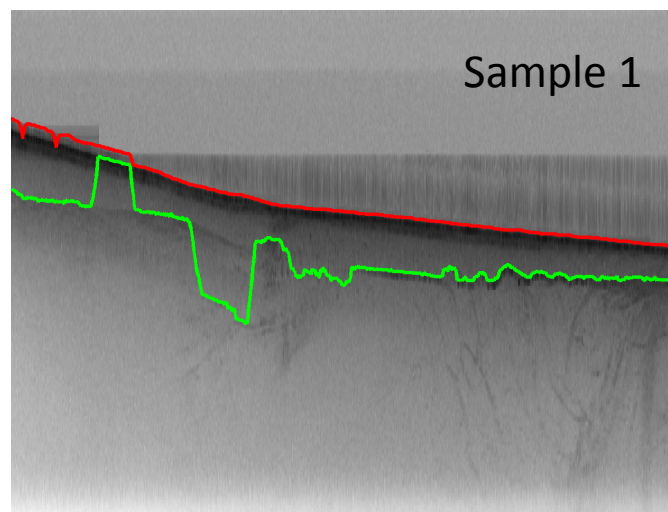
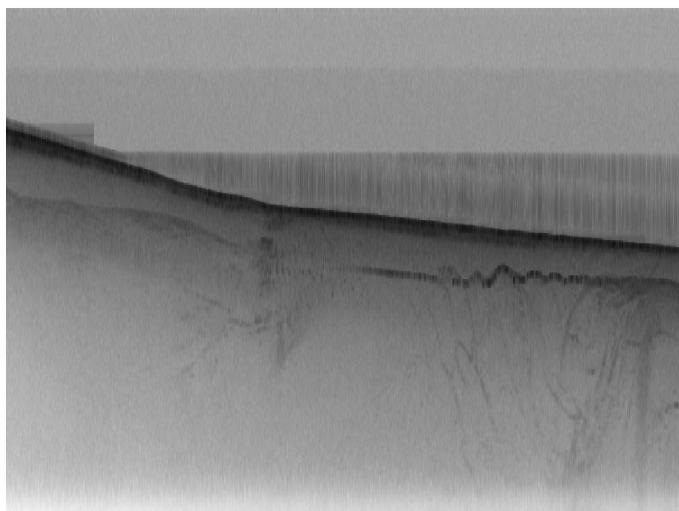


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# Sampling from the posterior

- Instead of maximizing  $P(L/I)$ , sample from it



# Quantitative results

- Comparison against simple baselines:
  - **Fixed** simply draws a straight line at mean layer depth
  - **AppearOnly** maximizes likelihood term only

	Air-ice boundary		Ice-terrain boundary	
	Mean Err	Mean SE	Mean Err	Mean SE
Fixed	69.0	10955.9	89.7	14975.2
AppearOnly	19.6	2949.8	42.1	7686.2
Our approach	14.1	1719.6	32.0	5078.9

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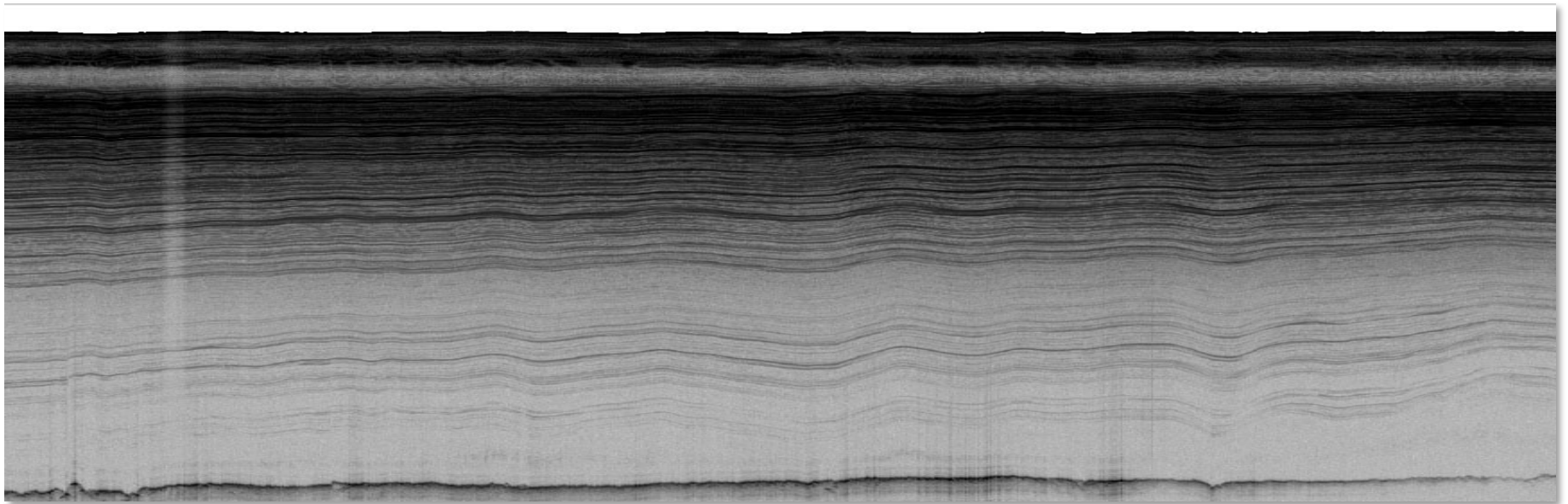
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- Further improvement with human interaction:

Ours, 1 pt	11.1	926.5	22.3	2652.5
Ours, 2 pts	10.1	718.6	18.3	1927.9
Ours, 3 pts	9.6	602.8	15.7	1470.2

# Summary and Future work

- We present a probabilistic technique for ice sheet layer-finding from radar echograms
  - Inference is robust to noise and very fast
  - Parameters can be learned from training data
  - Easily include evidence from external sources
- Ongoing work: Internal layer-finding



***Thanks!***

More information available at:

<http://vision.soic.indiana.edu/icelayers/>

This work was supported in part by:

