# New Possibilities of the Interpretation Seismic and Logging Data by Machine Learning Based on the RTH's Attributes


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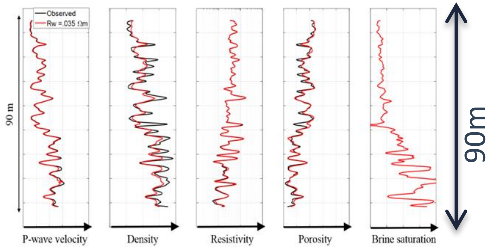
# Outline

- Motivation
- About Reverse Time Holography (RTH) method
- RTH’s attributes & logging data comparison
- Horizon picking based on the DeconvNet NN
- Clustering based on RTM & RTH attribute
- Conclusions

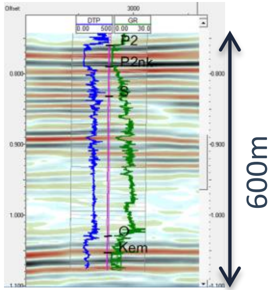
# Motivation of using the new RTH attributes

Conventional machine learning procedure of logging data and seismic attributes has (among others) the two main features (problems):

(i) Spatial resolution of well data and conventional seismic data is quit differ (seismic downscaling)

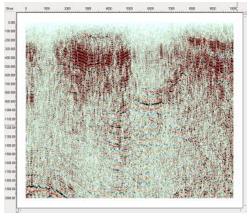



VS

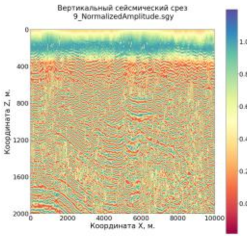



wavelength=velocity/ frequency

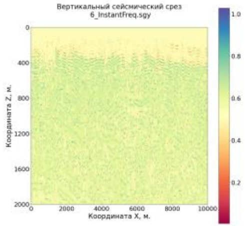
(i) All conventional seismic attributes are calculated from the same migration image (RTM, Kirchhoff)



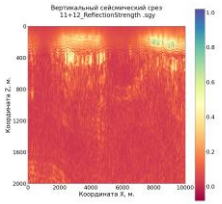
RTM



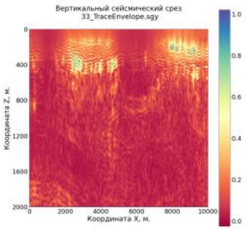

NormalizedAmplitude



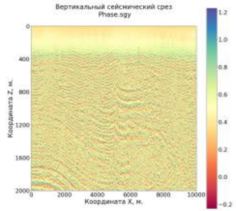

InstantFreq




ReflectionStrength




TraceEnvelope




Phase

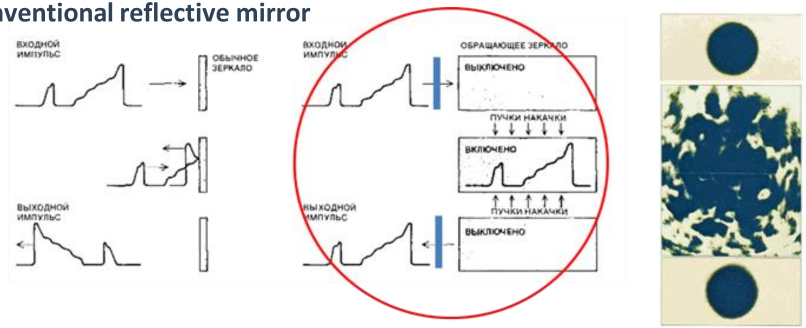
# About Reverse Time Holography (RTH) method

## *Two Main Fundamental Physic Prerequisites of RTH Approach*

I. Reverse time mirror (1972 ,B.Y. Zeldovich's team)

**Conventional reflective mirror**

**Reverse time mirror**

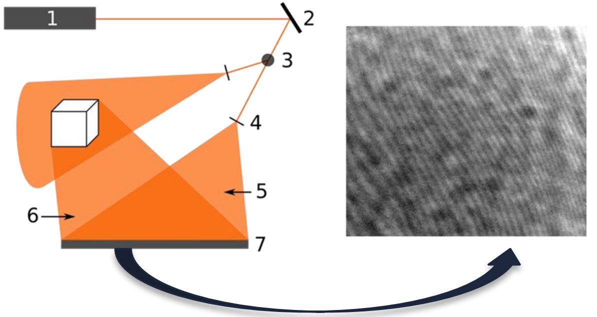



Muddy plate

Zel'dovich B.Ya., Popovichev, Ragulsky VV, Fayzullov FS, 1972, On the relationship between the wavefronts of reflected and exciting light in stimulated Mandelstam-Bryullen scattering. Letters to JETP, vol. 15, No. 3 pp. 160-164.

II. Two beams interferometry in Gabor’s optical holography (1948)

Photographic plate



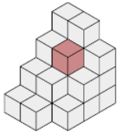

## *Main Mathematical & Computer Prerequisites of RTH Approach*

- Theories of adjoint equations and reversing the wave field in time
- Parallel Computing & Supercomputers
- Extra large data processing

# RTH data processing workflow

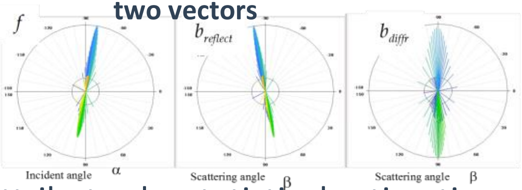
The seismic voxel-based attributes estimation by the RTH method is carried out in two stages for each voxel:

1. Full **Decomposition** (Vector Domain Common Image Gathers dataset - simile photograph plate in optical holography), based on two vectors : the incident wave vector and the time-reversed "backward" scattered wave



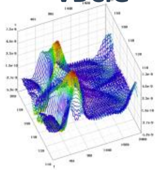
Voxel

two vectors



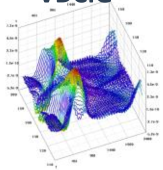

***Decomposition***

VDCIG



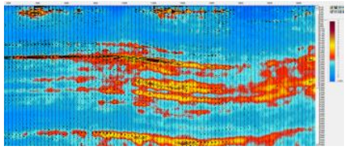
2. **Synthesis-** seismic attributes by statistical estimation of multidimensional dataset

VDCIG



***Synthesis***

RTH attributes



**RTH approach features**:

- No reflectivity-based
- Voxel-based
- Static corrections free
- *Attributes independent*
- Acquisition robust
- Scatter-based
- Simple initial model
- Natural multi-attributing
- Direct voxel-based velocity estimation

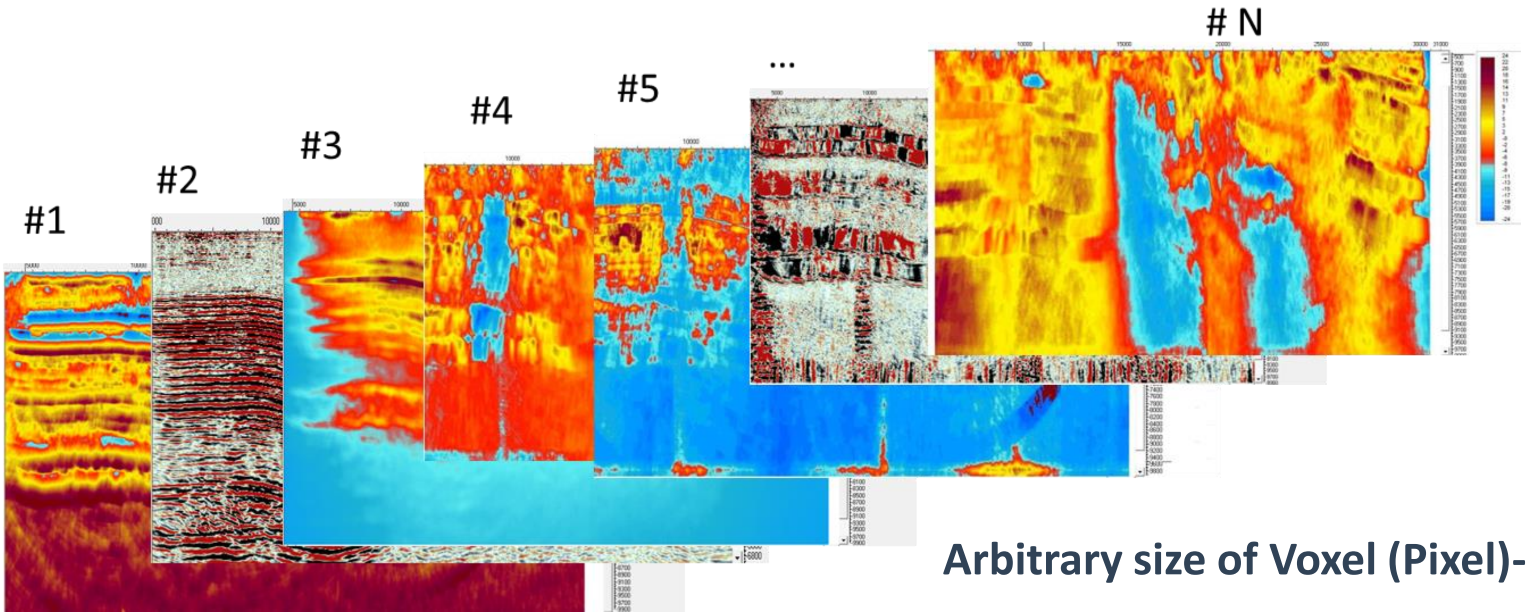
**3D CDP Gathers** → **Vector Domain Common Image Gathers** → **RTH Voxel-based Attributes**

$R^5 : p(x,t,x_s)$

$R^{10} : (|f|,|b|\alpha,\beta,\omega_f,\omega_b,t,s,\varphi,\theta)$

# RTH attributes

RTH attributes are calculated *simultaneously and independently* based on VDCIG data and forms a vector of length N (N> 100) in *each* voxel of medium

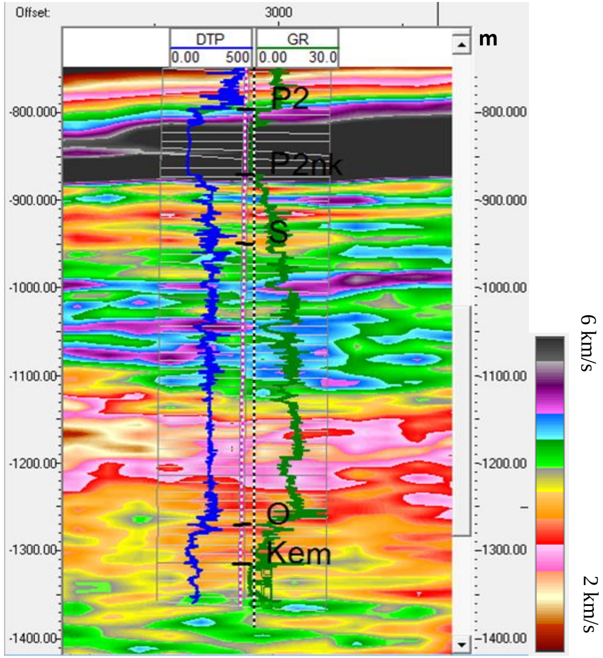



**List of RTH attributes:**

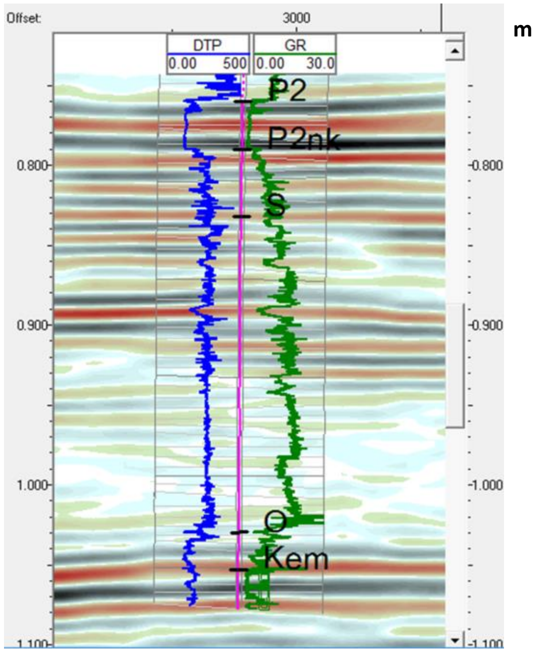
- Diffractivity
- Velocity
- Reflectivity
- Opening Angle
- Dip
- Frequency
- AVO
- Azimuthal Angle
- Polar Angle
- Angles Correlation
- etc.

**Arbitrary size of Voxel (Pixel)- up 1 meter**

# RTH & Logging data comparison

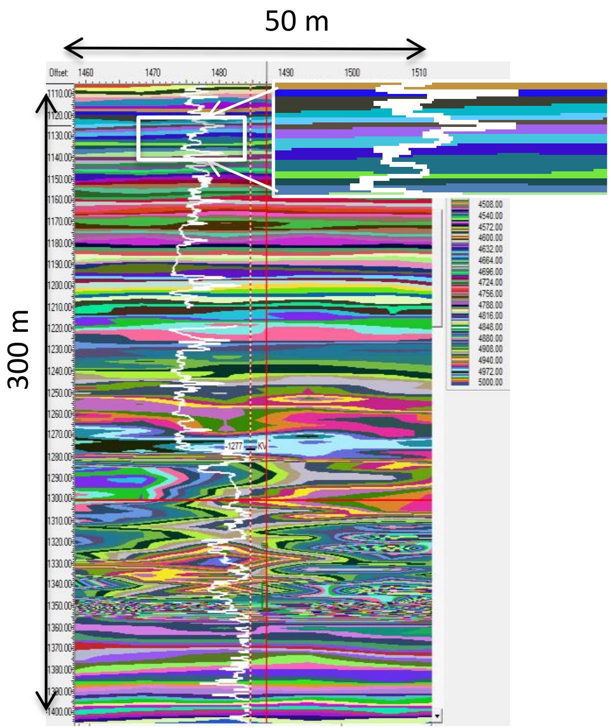



RTH Velocity



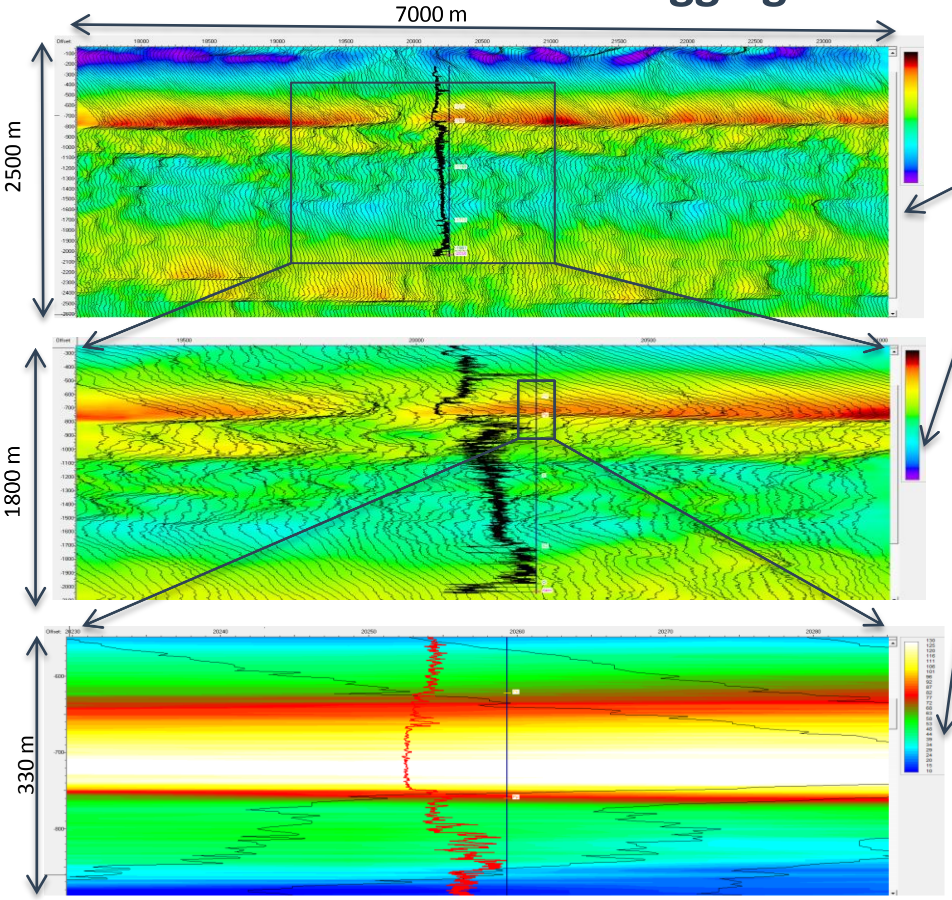

PSTM

Comparison of RTH velocity with PSTM. Dark color palette - Perm high velocity deposits. Baltic syneclise. Pixel size is 25x5 m.

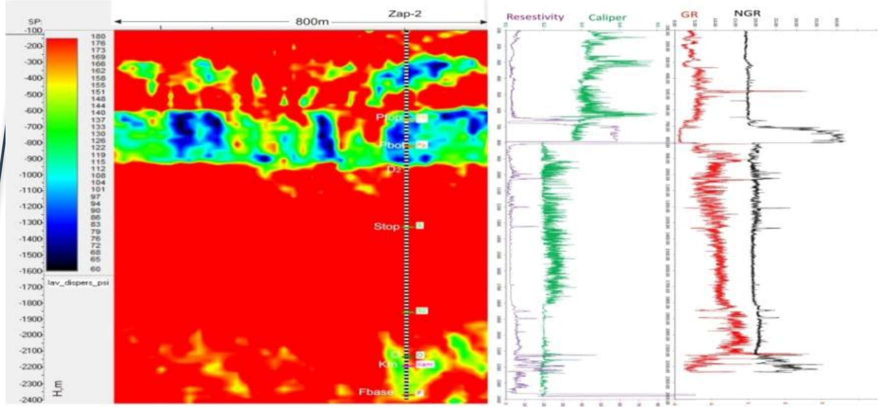



Vertical section of the RTH velocity cube. Voxel size is 12,5x12,5x2,5 m. Depths are from 1100 up to1400 m. Velocity scale is from 4200 up to 5000 m/s. The white line is the Gamma Ray (GR) log. Eastern Siberia. 200 Random color bars IHS.

# RTH & Logging data comparison

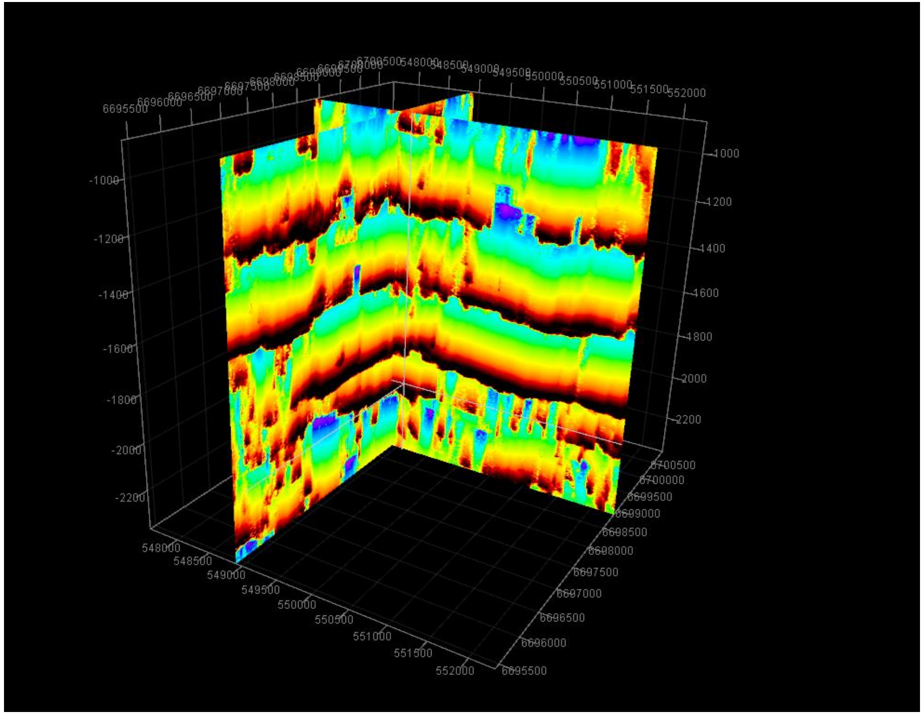



**Zooming cascade.** 2D RTH velocity with overlay of the GR curve. The size of the velocity pixel is 12.5x2.5 m. The red color of the palette is high-velocity deposits of Perm. Baltic Syneclise.

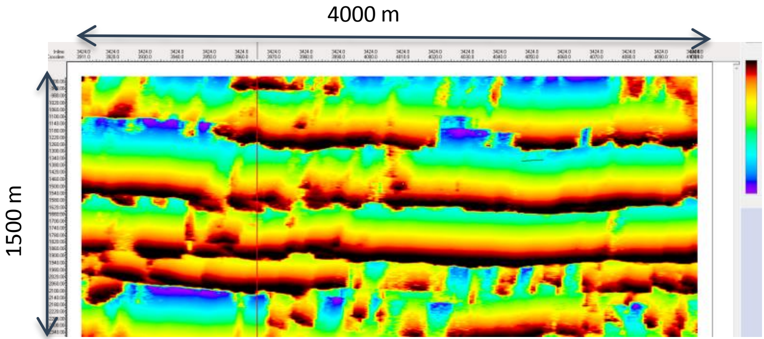



The correlation of the Dip Angle Variance with the data of logging measurements. Log data from left to right: resistivity log, caliper log, gamma ray log, neutron gamma log

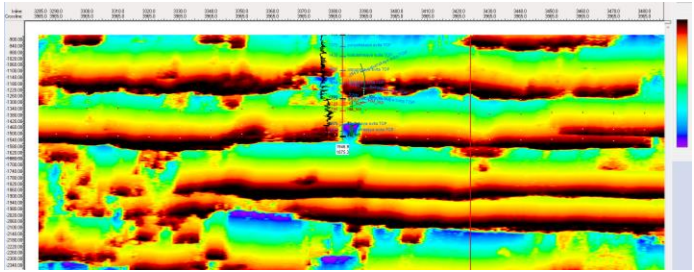
# Automation picking problem based on high resolution 3D RTH-velocity




3D RTH-velocity cube




RTH-velocity. Inline



RTH-velocity. Crossline

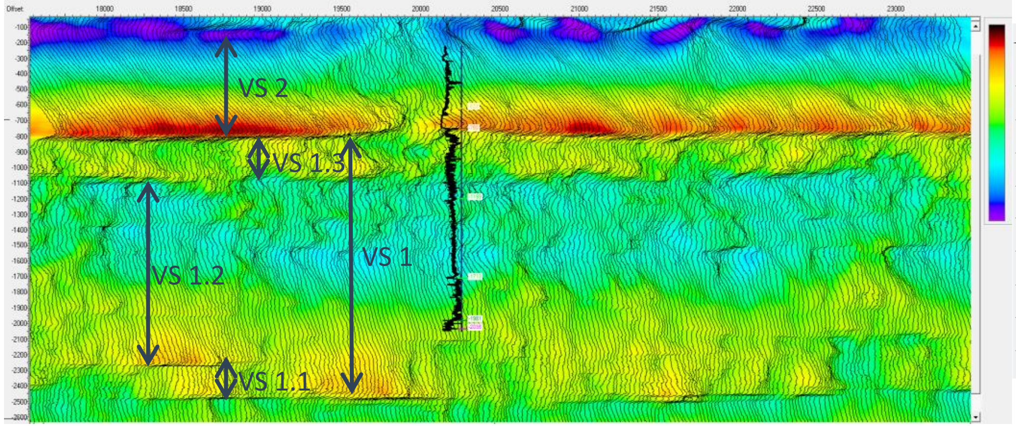
Voxel size is 12,5x12,5x2,5m

# RTH-Velocity Stratum Concept

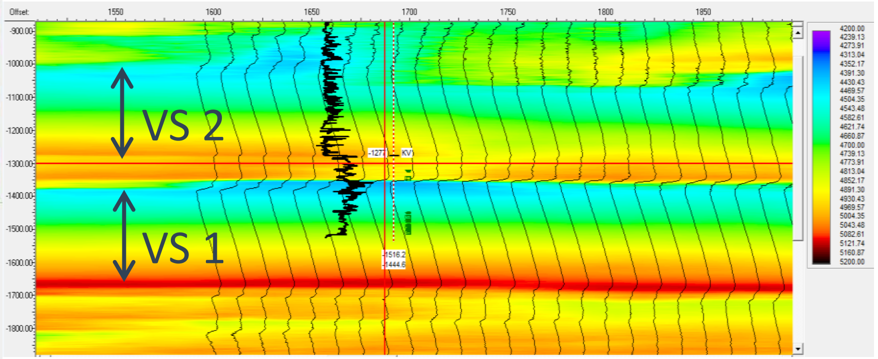
**The concept of the RTH-Velocity Stratum (VS) is based on:**

- Similarity velocity patterns of the RTH-velocity variation within one RTH-velocity stratum both in depth and lateral
- Separation of RTH-velocity stratums from each other in depth by **VS-boundaries** with sharp velocity inversion
- Hierarchies and nesting of RTH-velocity stratums of different thicknesses

**Examples of the RTH-velocity stratums:**



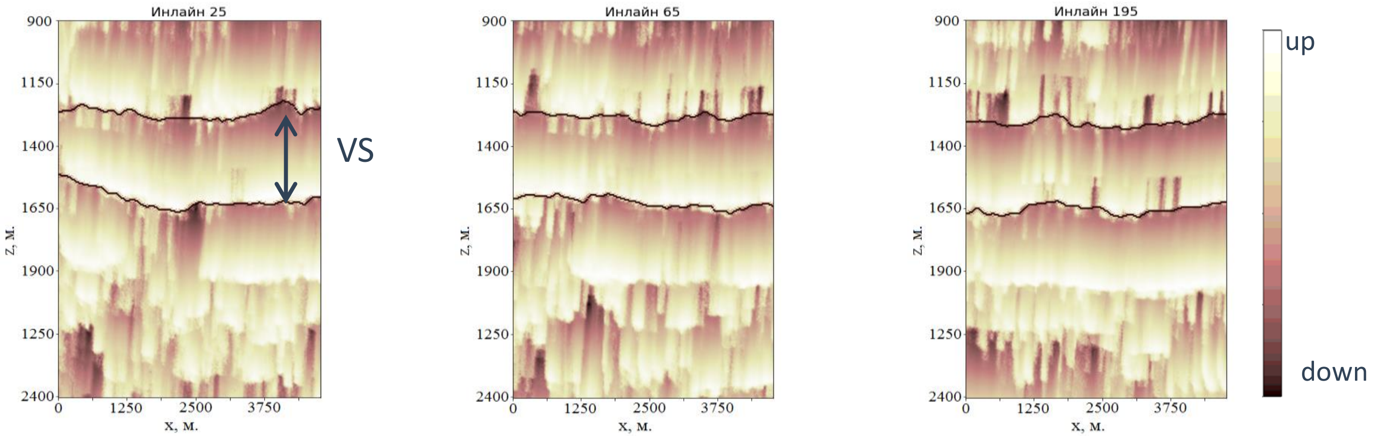

RTH-velocity. Depth resolution - 2.5 meters



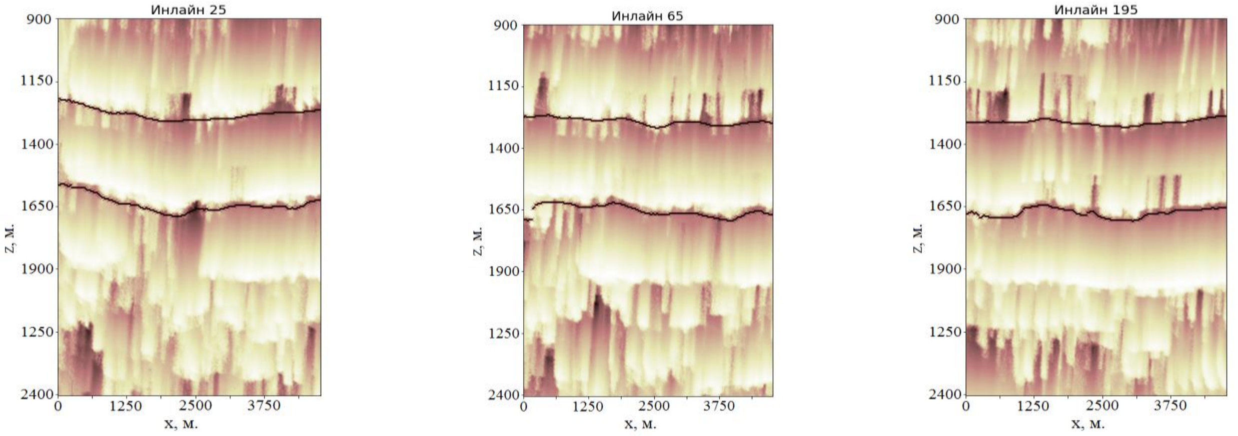

RTH-velocity. Depth resolution - 5 meters

# Automation picking RTH VS-boundaries by the DeconvNet neuron network

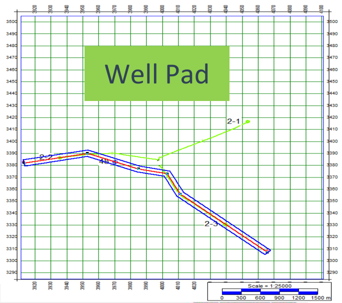
*VS-boundaries by manually picking*

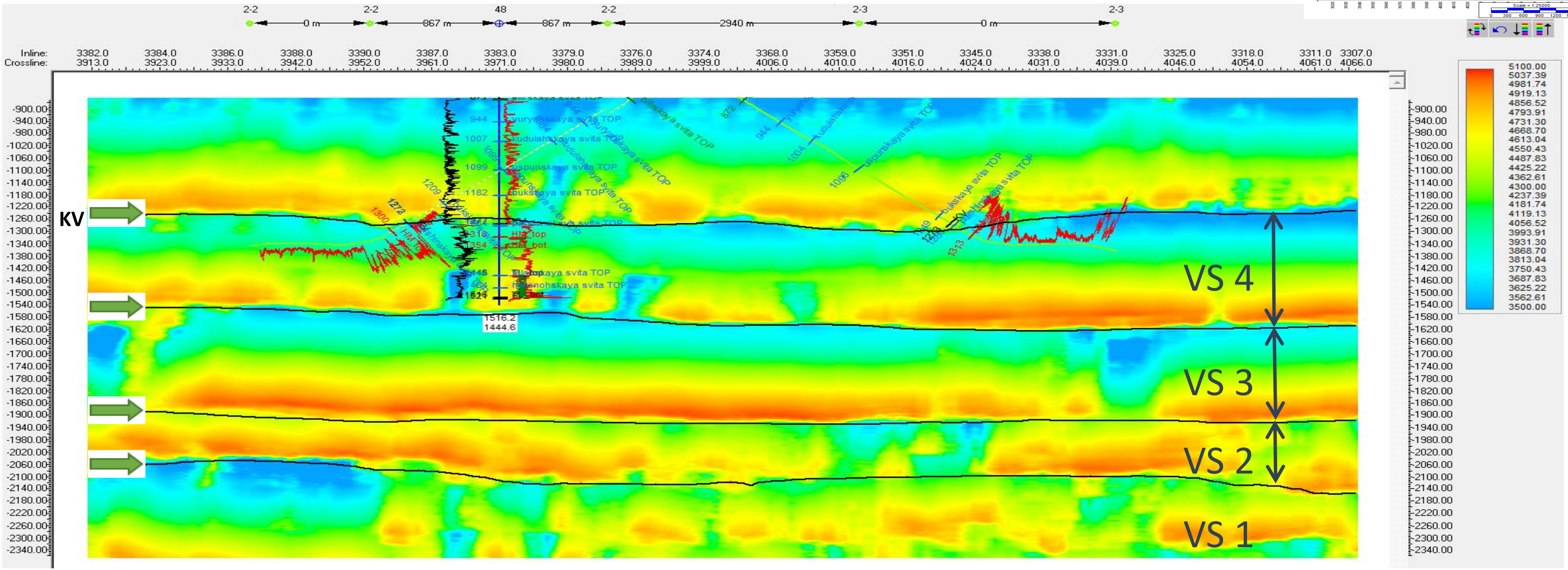



*VS-boundaries by DeconvNet ML picking*



# Case study. RTH VS-boundaries: georeferencing the RTH-velocity cube according the well logging data

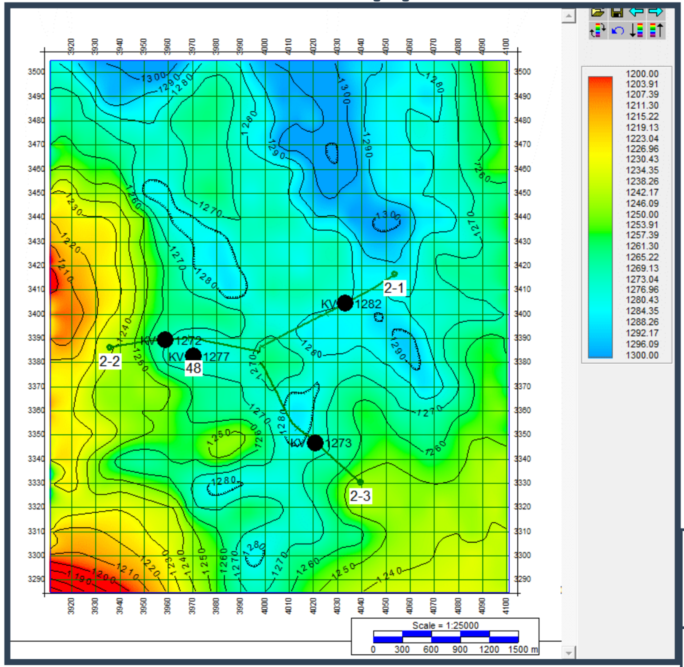



RTH-velocity scale, m / s

Voxel size is 12,5x12,5x2,5m

# Comparison the KV structural map constructed by velocity-based RTH approach with the conventional PSDM map

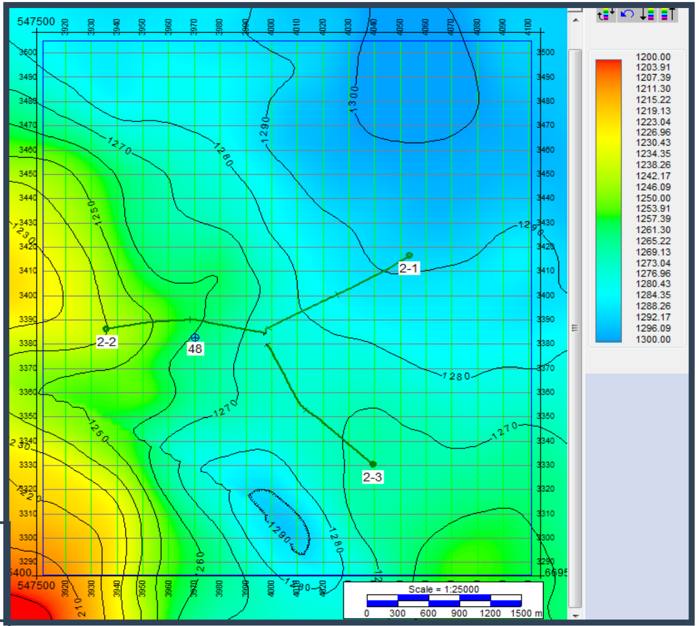



RTH map, m

Voxel size is 12,5x12,5x2,5m

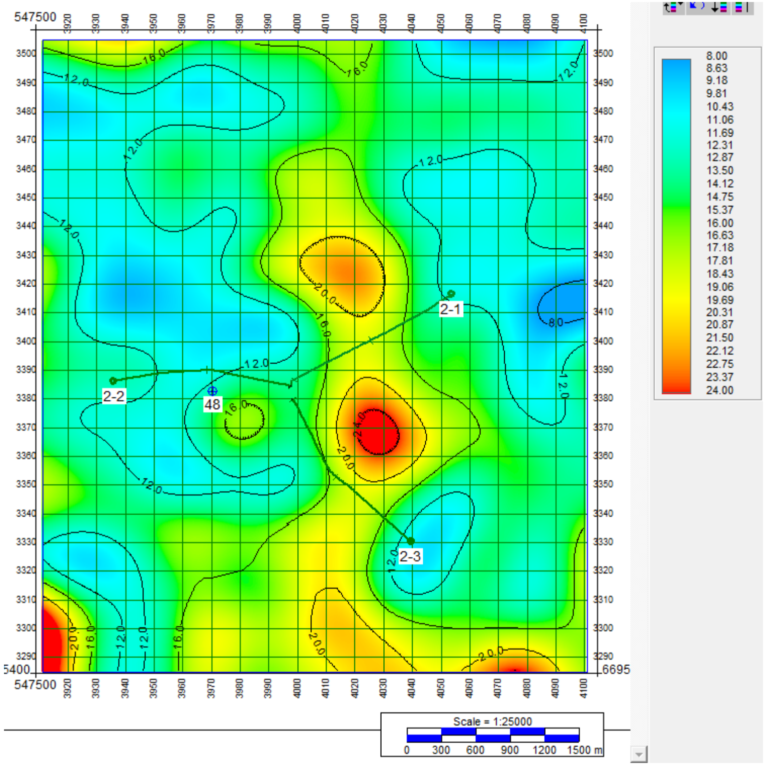
Black dots on the map - KV's depth by inclinometry

| Well # | Depth, well (m) | Depth, RTH map (m) | Error (m) |
|---|---|---|---|
| 48 | 1277 | 1272 | 5 |
| 2-1 | 1282 | 1280 | 2 |
| 2-2 | 1272 | 1271 | 1 |
| 2-3 | 1273 | 1274 | 1 |



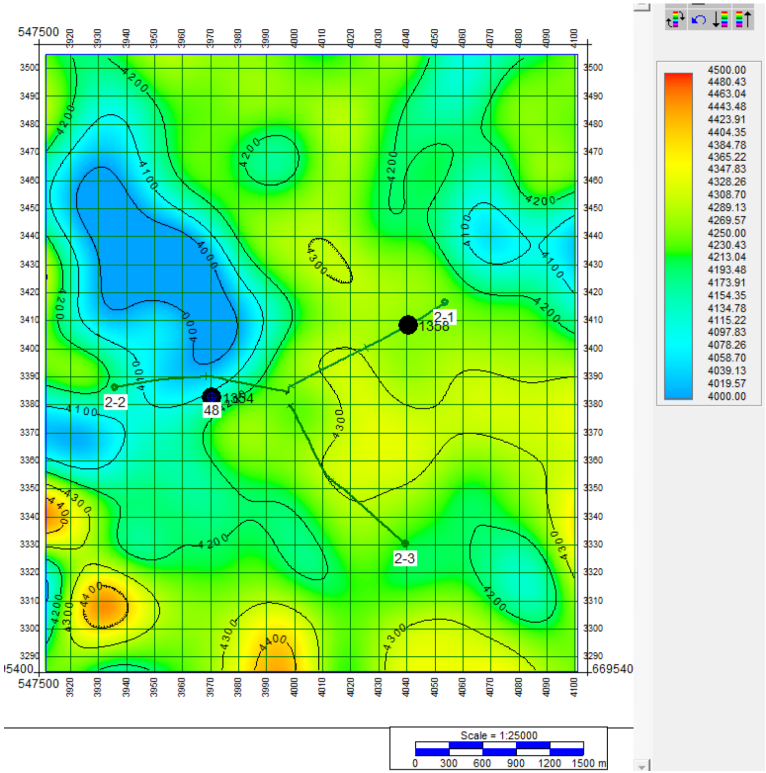

PSDM map, m

# Velocity-based mapping the productive Hm2 horizon



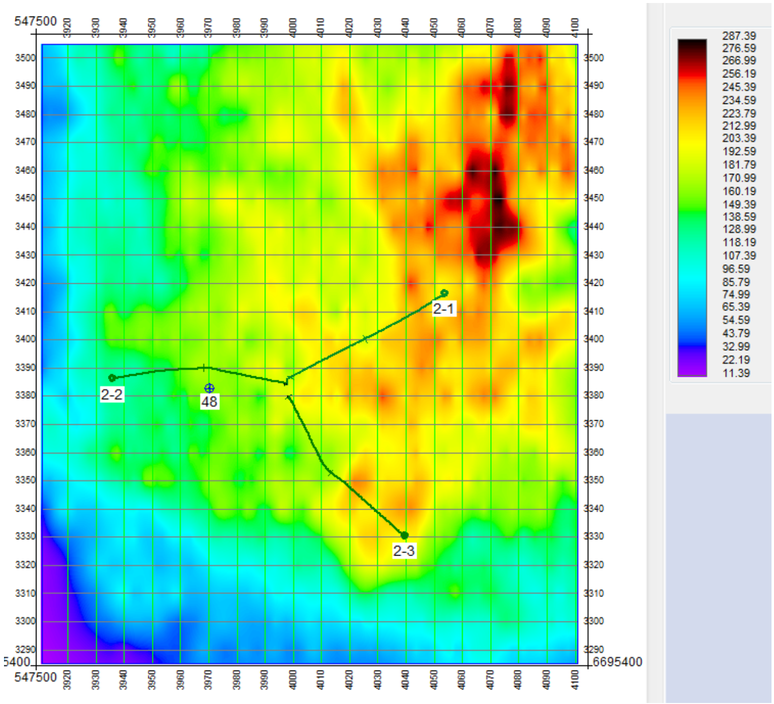

Thickness map, meters

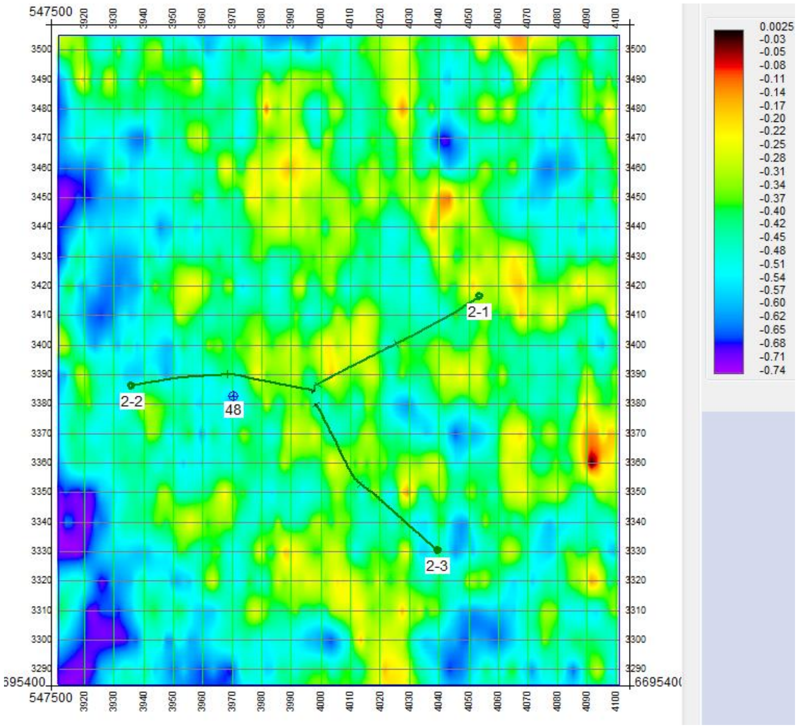
Voxel size is 12,5x12,5x2,5m




Velocity map, meters per second

# RTH-attributes in productive Hm2 horizon




Diffractivity map

Voxel size is 12,5x12,5x2,5m

Angle Correlation map

# RTH and  Machine Learning

Machine Learning

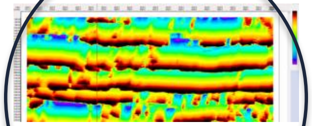
Supervised Learning

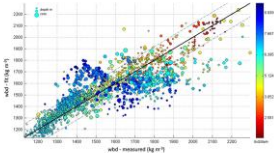
Unsupervised Learning

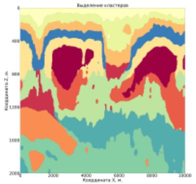
Classification

Regression

Clustering







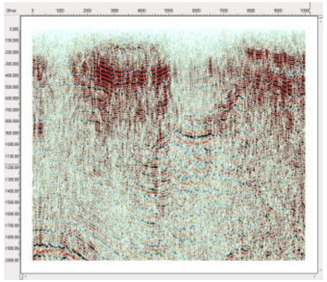
# List of RTM-based and RTH-based attributes. RTM & RTH Clustering

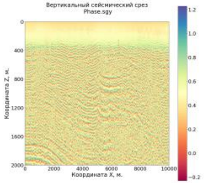
## Conventional RTM-based attributes

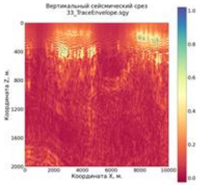
1. RTM
2. PseudoRelief
3. InstantFreq
4. InstantPhase
5. InstantQuality
6. BandWidth
7. ReflectionStrength
8. WaveletApparentPolarity
9. NormalizedAmplitude
10. AverageEnergy
11. DominantWavenumber
12. RunningSum
13. ChaoticReflection
14. TraceEnvelope
15. RelativeAcousticImpedance

…

22. TraceEnvelope





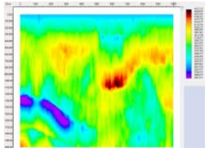


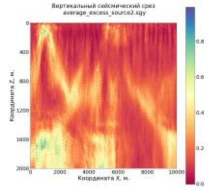
## RTH-based attributes

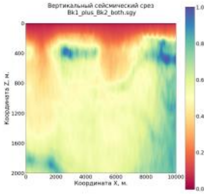
1. AnisotropySource
2. AssimetryFrequency2
3. AssimetryKsi2
4. AssimetrySource
5. TrueRTM1_plus_TrueRTM2_both
6. ResidualKsi2
7. Refl1_plus_Refl2_both
8. OpeningAngleDipCorrelation2
9. Back1_plus_Back2_both
10. AverageTime2
11. AverageKsi2
12. AverageFrequency2
13. AverageExcessTime2
14. AverageAssimetryTime2
15. AverageExcessKsi2

…

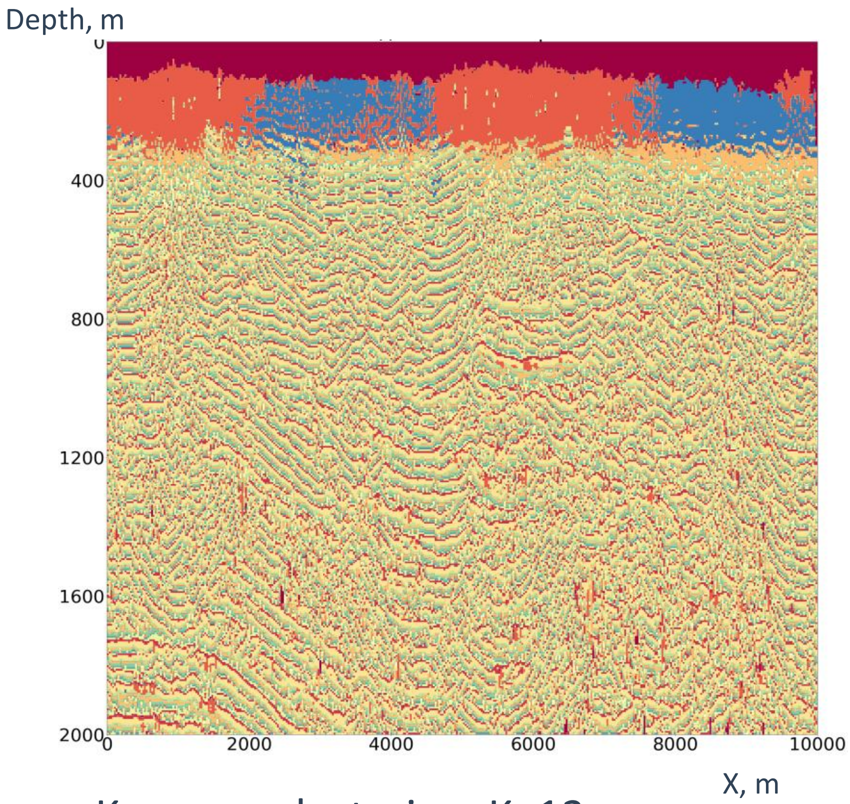
22. AverageAssimetrySource2



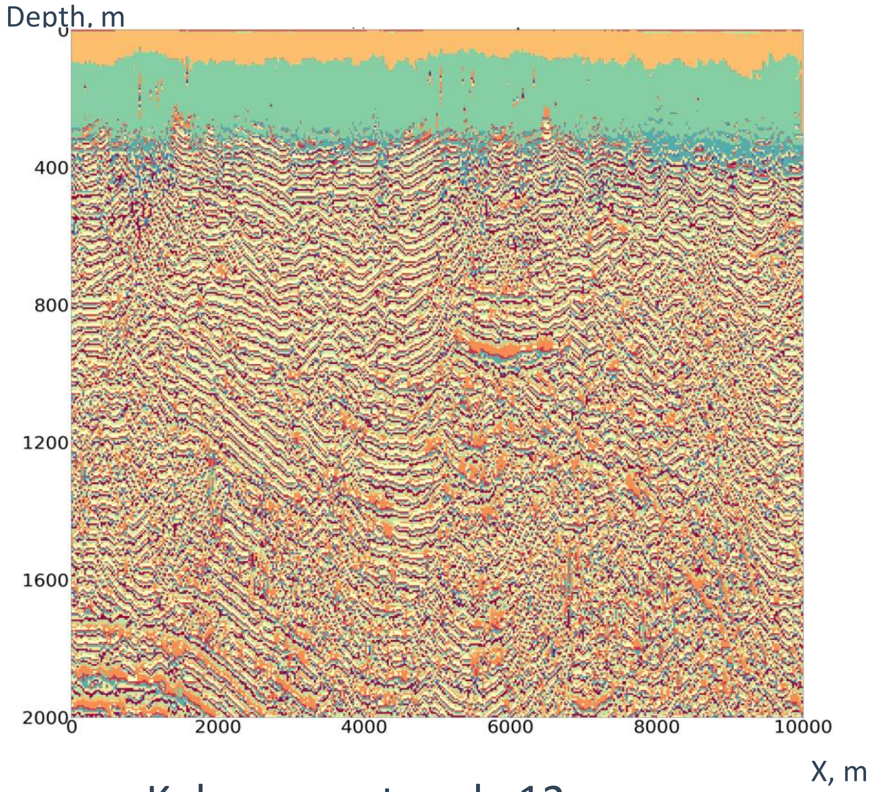




# Unsupervised learning. Clustering based on conventional RTM-based attributes

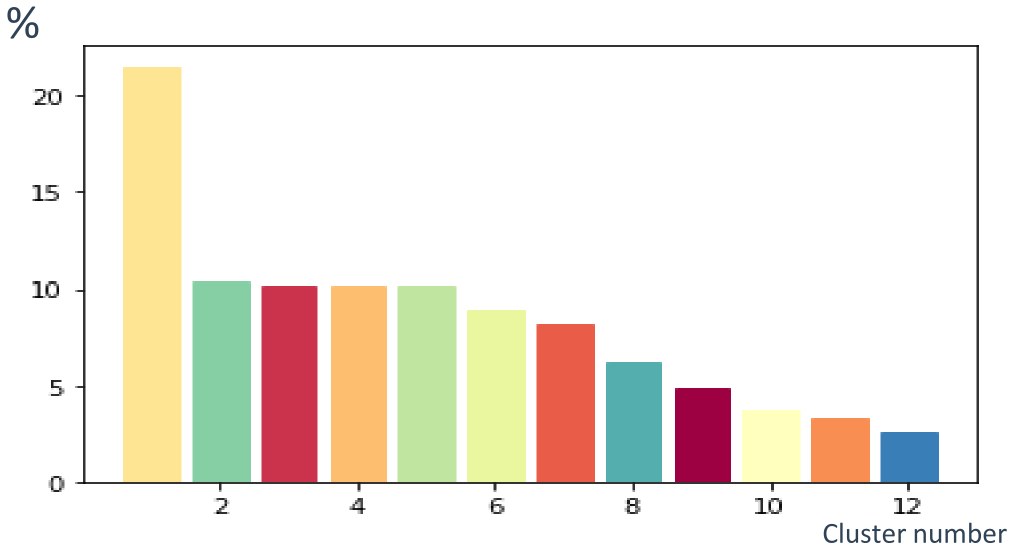



K-means clustering. K=12

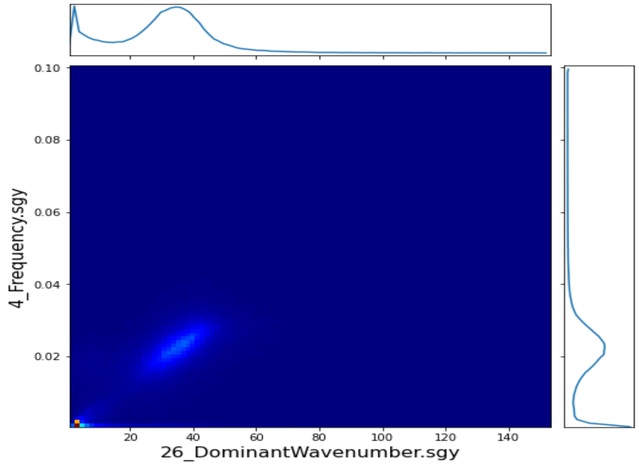



Kohonen network. 12 neurons

# Unsupervised learning. Clustering based on conventional RTM-based attributes

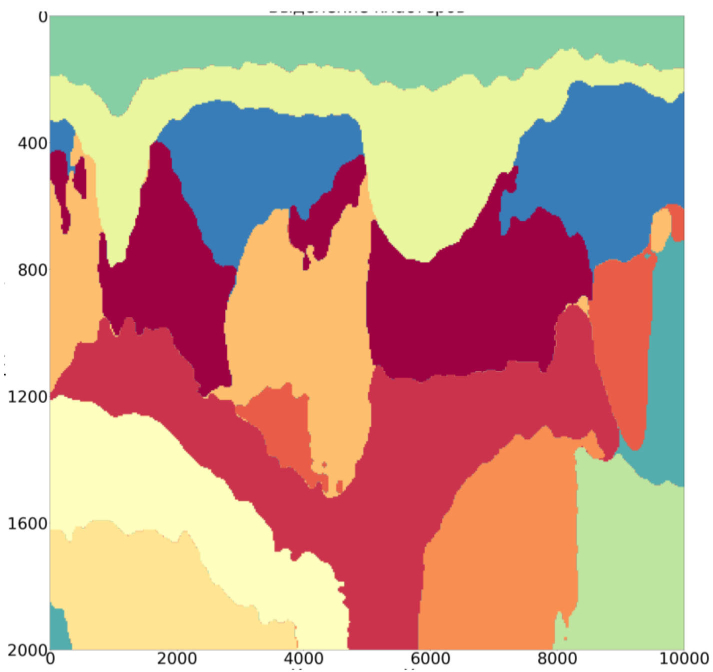



Histogram. K-means clustering

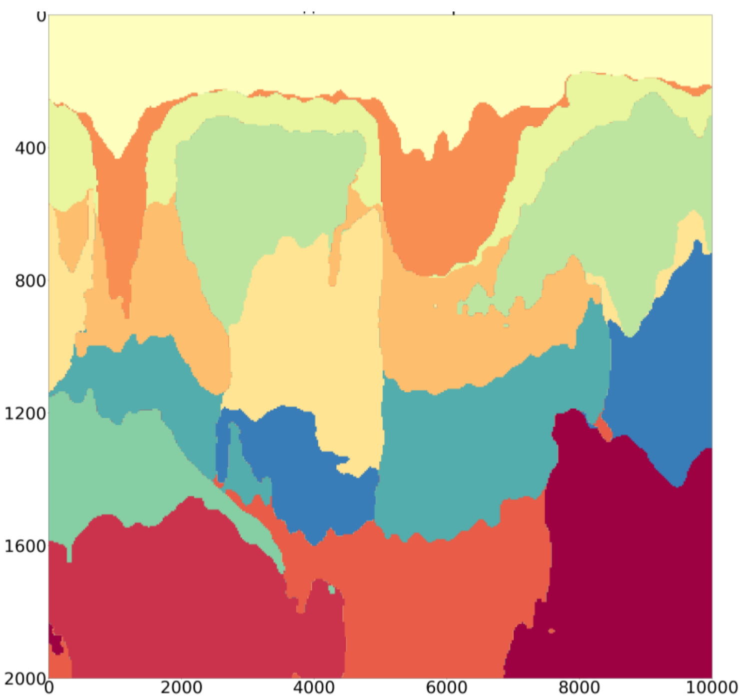



Cross correlation example

# Unsupervised learning. Clustering based on  RTH-based attributes

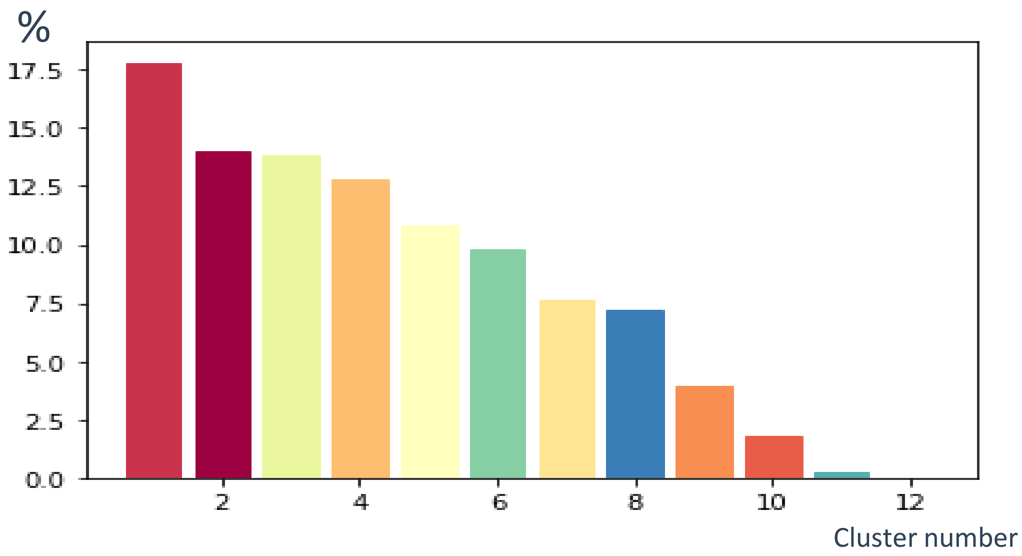



K-means. K=12

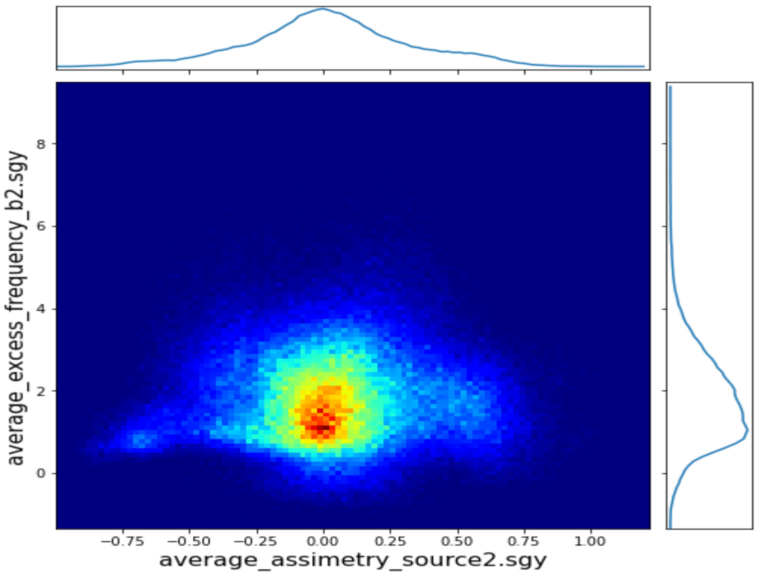



Kohonen network. 12 neurons

# Unsupervised learning. Clustering based on RTH-based attributes



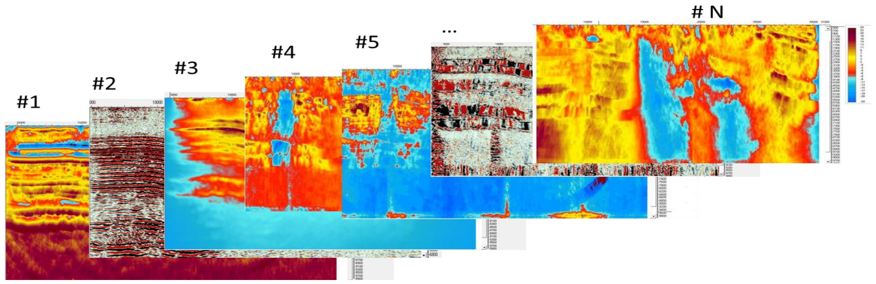

Histogram. K-means clustering



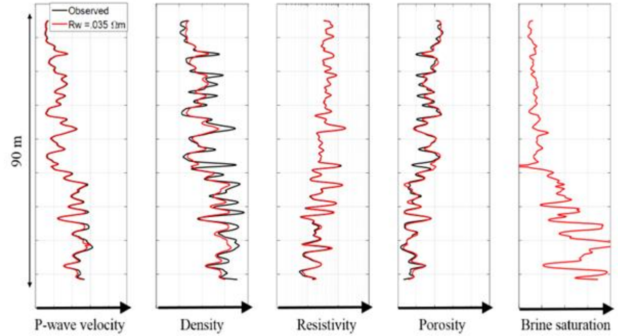

Cross correlation example

# Next step: Supervised machine learning based on RTM attributes and logging data

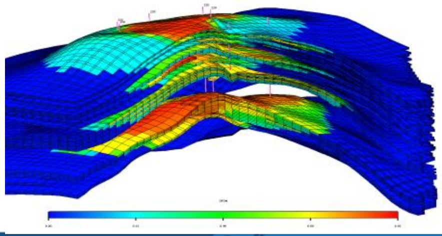
Synchronous calculation of RTH attributes in each voxel of a geological environment up to 1 meter in size

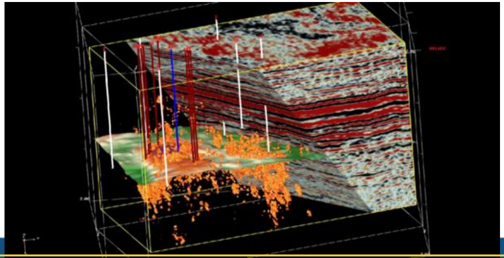



Geophysical well logging data




Machine learning to predict hydrocarbon deposits in the entire geological environment



## Conclusions

- The of joint ML-based interpretation of logging data and seismic attributes require from them the same resolution in depth and at the same time the seismic attributes should be as independent of each other as possible
- It seems that the new RTH attributes, in contrast to conventional attributes which is built on migration images, have the necessary properties for ML
- Example of application the robust automatic piking the RTH-velocity boundaries by ML is presented
- The new high precision RTH-based solution of mapping problem is proposed

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# Thanks!

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