Roof Condition: Added intelligence from Machine Learning and Imagery

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CAS Ratemaking Product Modeling Seminar
Boston March, 2019

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Roof Intelligence
Use Cases

Pricing & Eligibility Decisioning

Comprehensive roof intelligence for price differentiation and product eligibility

Underwriting Decisioning

Effective inspection decision engine

- No Inspection
- Virtual Inspection – Imagery
- Physical Inspection –Boots on the Ground

Claims Management

Predict Claims

- Inspect at renewal
- Rating at renewal

Claim Validation

- Likely to incur claim
- Identify potential fraudulent claims

Individual Roof Intelligence Components

ROOF AGE / PERMIT

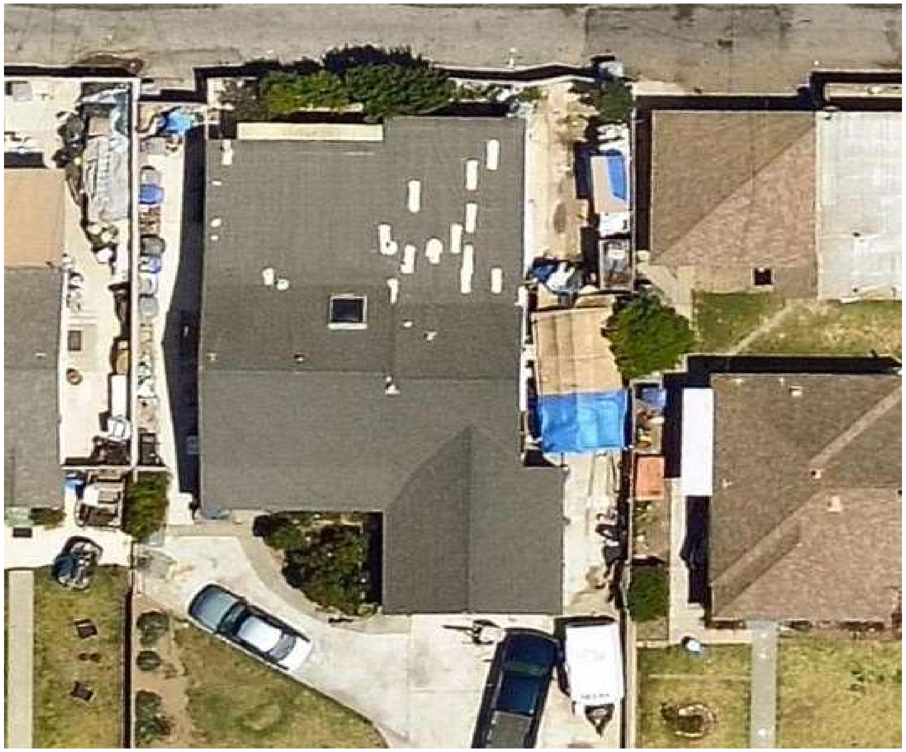
Roof Replacement
PERMIT: BX200902016

YEAR: 2015

IMAGERY

AERIAL: 2” – 6” resolution
DRONE: 1” resolution

In progress: Machine Learning to Extract Property Attributes & Condition



HAIL

Event History	
Less than 2.00”	3
Greater than 2.00”	0
Recent Event	04/16/2018
Largest Event	07/23/2015

ROOF SYSTEM DATA

COST: $15,000
MATERIAL: Shingle
ROOF SIZE: 1,600 Sq. Ft

Comprehensive Roof Intelligence

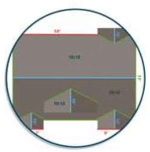
Gain Competitive Edge & Market Differentiation

Build Roof Score: predict roof condition, mitigate risk

Hazard & Geospatial Layers

+

Roof Characteristics



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Property Characteristics

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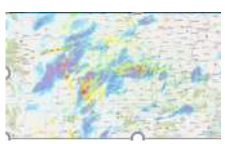
Climate Data



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Property Address					
Policy Id	**Street Address**	**City**	**State**	**Zip**	**Roof Condition Score**
1	1234 N 24th St	Mesa	AZ	85213	672
2	1234 Yorktown Dr	Lodi	CA	95242	853
3	1234 Castle Cliff Pl	Silver Spring	MD	20904	891
4	1234 March Dr	Denver	CO	80239	362
5	1234 16th Pl SE	Bellevue	WA	98006	283
6	1234 Cedar Ln	Longview	WA	98632	676
7	1234 NW Oak Ave	Corvallis	OR	97330	505
8	1234 Prospect St	Santa Cruz	CA	95062	942
9	1234 Louisiana Ave S	Bloomington	MN	55438	555
10	1234 Salmon Dr	Carmel	IN	46033	688
...	...	...	...	...	...

Apply Roof Intelligence

Establish Pricing

Create pricing based on score

Apply at New Business & Renewal

Integrate score and apply rate at new business and renewal

Underwriting

Automated UW Decisioning

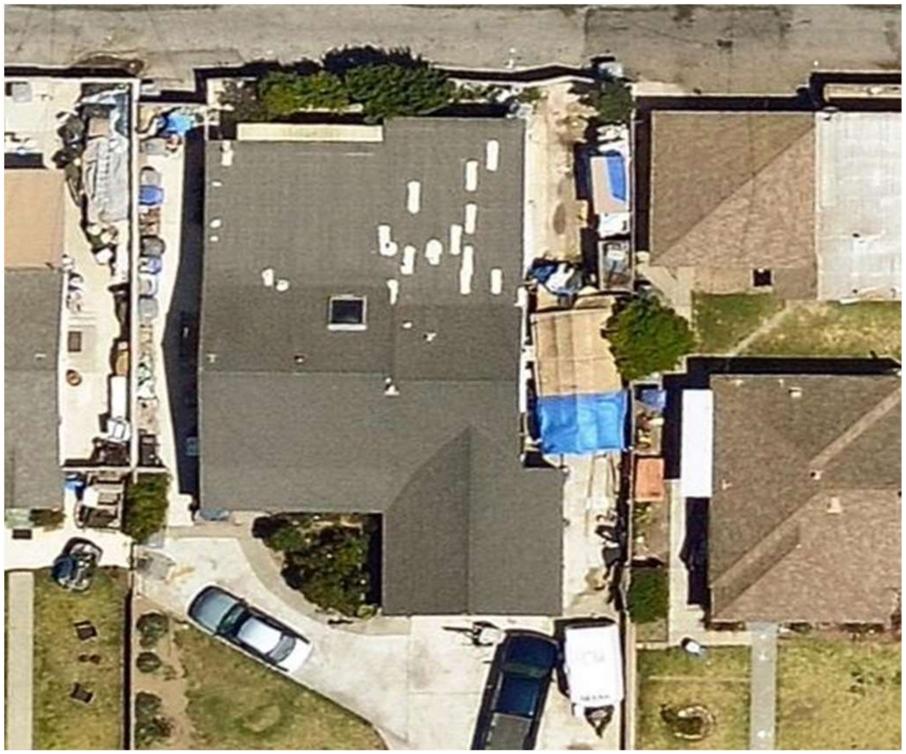
- Score + Roof Age + Hail Insight
    - Virtual Inspection – Imagery
    - Physical Inspection –Boots on the Ground

Roof Intelligence: The Pictures

Taylor Brown
CoreLogic

Images

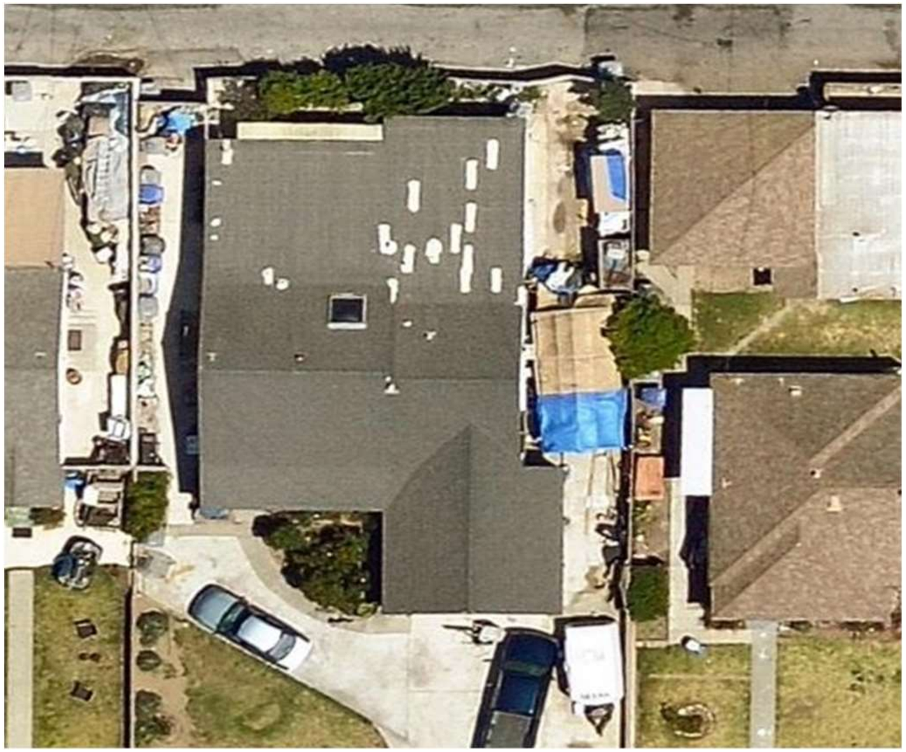
A picture is worth 1000 words



- Words:
  - ?

Images

A picture is worth 1000 words



- Words:
  - Asphalt Shingle
  - Garage
  - Gable
    - Measure Slope
  - Skylight
    - How many/where?
  - Tree overhang
  - Missing Shingles
  - How big is the roof?
    - Outline/Surface Area
  - How storm resistant is it?
    - How much will it cost to replace?
    - What's the likelihood of a windstorm causing catastrophic failure?

Overview

1. Imagery
2. Deep Learning
3. Experiment

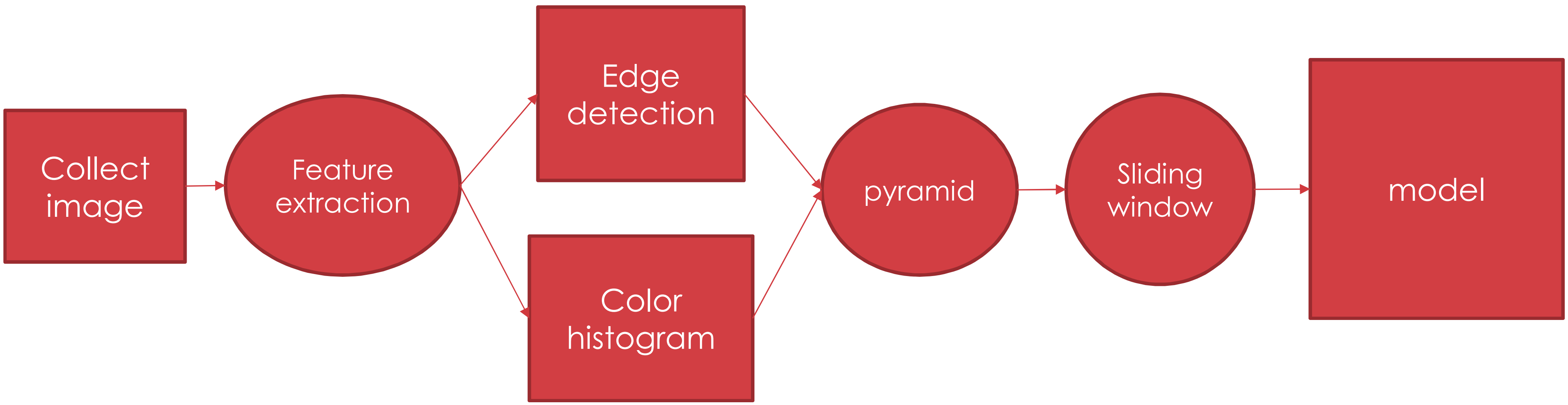
Imagery

Sources

- Overhead
  - Aerial
    - USGS made available digitally in the 1990s
  - Satellite
    - USGS made available in the 1970s
  - Drone
    - FAA allows commercial use in 2015
- Natural
  - Handheld camera
    - Digital cameras widely available in 1990s
  - Phone
    - Introduced in 2001

https://www.pexels.com/photo/blue-and-gray-concrete-house-with-attic-during-twilight-186077/

Imagery Pipeline (circa 2005)



Learning from imagery

- Data pipeline
  - Data input
  - Pre-Process
  - Extract features
  - Train model
    - Supervised
    - unsupervised

- Data input
  - Discretize real-world
  - Usually a camera
- Process features
  - Raw input
  - Edge/corner detection
  - Textures
  - colors
- Train model
  - Regression (logistic)
  - SVM
  - Neural network
  - clustering

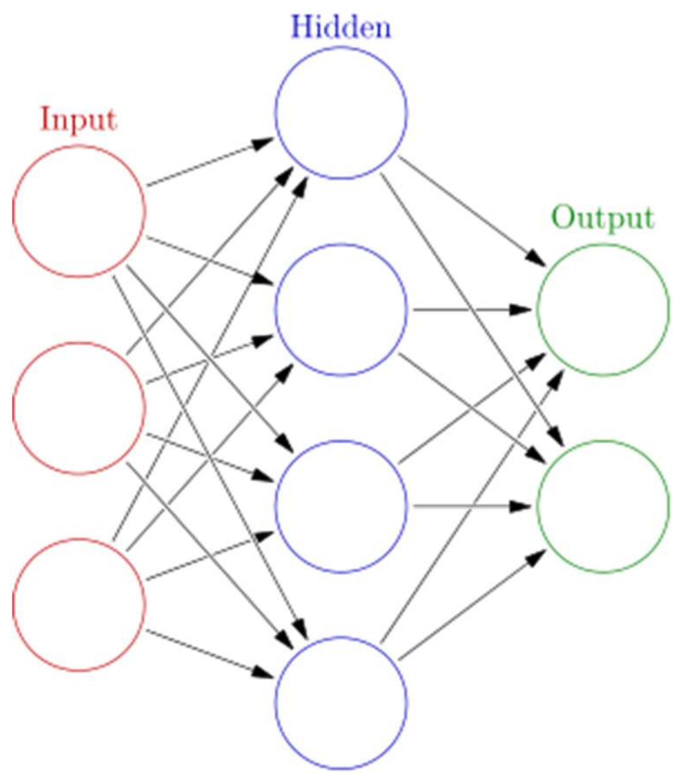
Deep Learning, or How To Understand the Black Box

To deal with a 14-dimensional space, visualize a 3-D space and say 'fourteen' to yourself very loudly. Everyone does it.

- Geoffrey Hinton ("Godfather of Deep Learning“)

Deep Learning

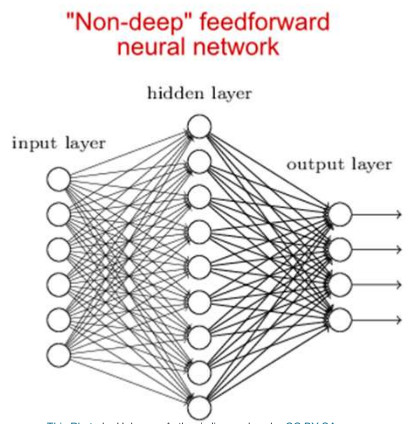
- What are Neural Networks?
  - Stacked layers of regression models, e.g. logistic regression, but usually has different function (Statistics 102)
    - Y = *f* (**w*x** +b)
  - Essentially, build out a series of logistic regressions in parallel.
    - This is a layer
  - You can then stack layers.
  - Training proceeds by using standard numerical optimization techniques – i.e. Stochastic Gradient Descent
    - Previous layers are trained through clever application of the chain rule (Calculus 102).

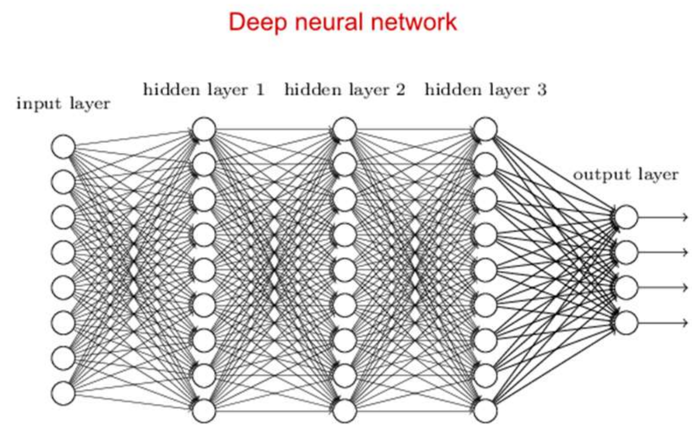


https://commons.wikimedia.org/wiki/File:Colored_neural_network.svg

Deep Learning

- What's Deep Learning?
  - Traditionally, it was impossible to train networks with more than 3 layers and have them do well.
  - Earlier work on neural networks (convolutional) created deeper networks that were vision specific.
  - Recent theoretical advances (Hinton, 2008) finally broke the 3 layer restriction for general neural networks.
  - Still incredibly slow to train for "small simple datasets"
  - Training was something of a 'dark art' few mastered

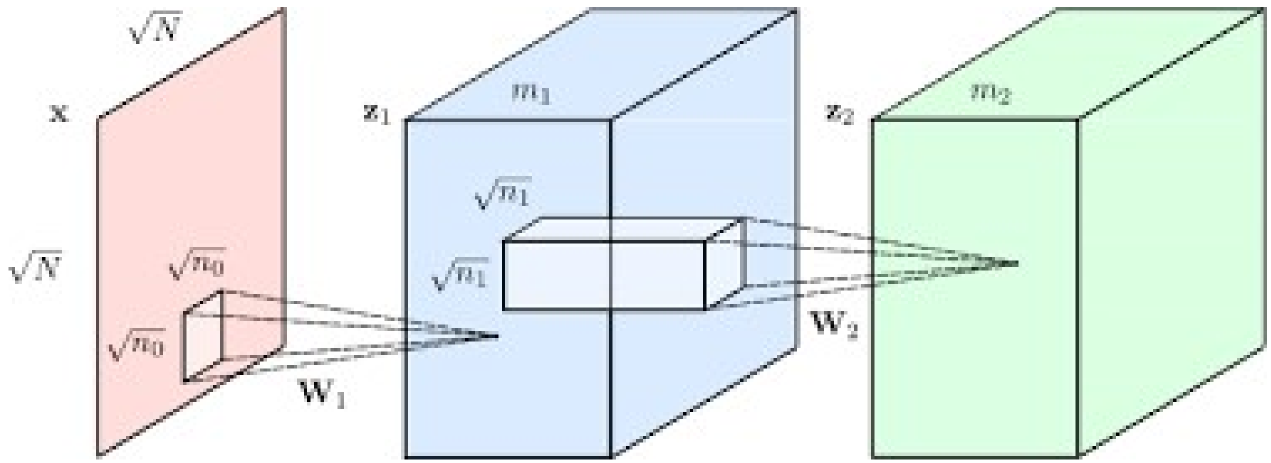




Deep Learning

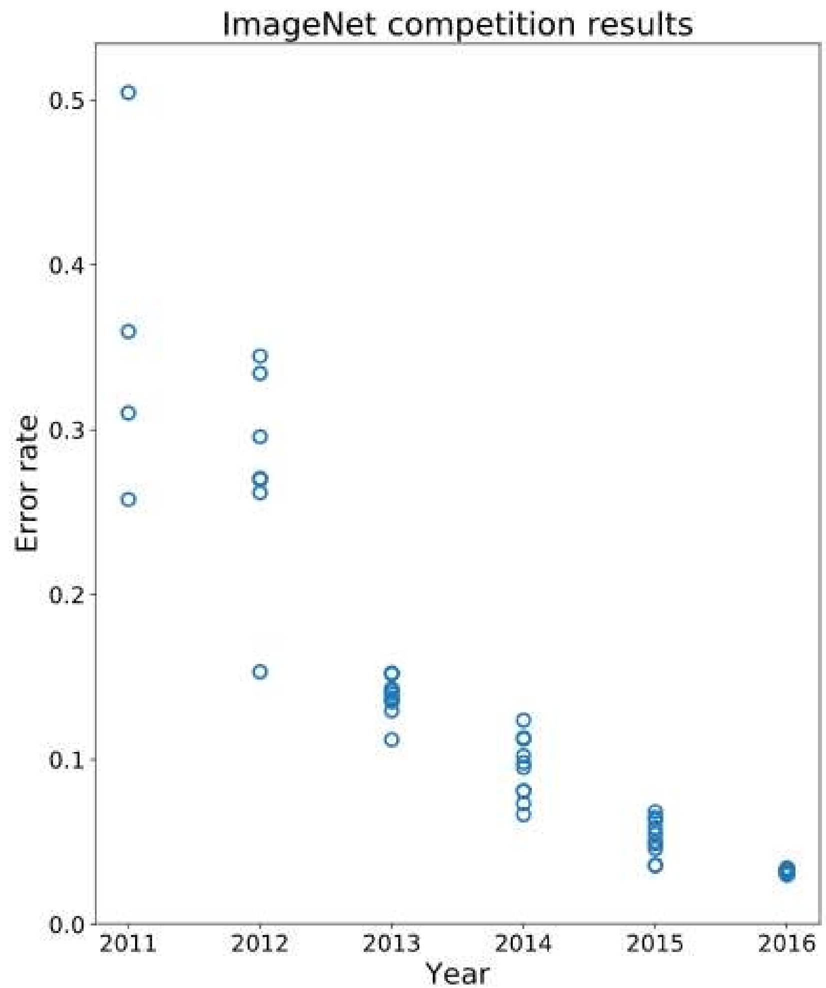
- Processing pipeline is difficult to optimize
- Can we teach the machine to do all this?

- Convolutional neural networks
  - Learns filters automatically
    - Edge detection built in (convolutions)
  - Model is a pyramid
    - Max pooling



Deep Learning

- Why now?
  - Imagenet competition (2011)
    - 1 million labeled images, 1000 classes
    - The Unreasonable Effectiveness of Data (Halevy 2009)
  - Specialized hardware (Nvidia GPU) enabled rapid training of previously difficult to train models (LeCunn, 1998)
    - GPU – Nvidia quotes 47X speedup vs CPU for the latest and best card
  - Krizhevsky (2012) won the ImageNet competition to great effect
    - Beat next best approach by 10% (absolute)
    - Released code publicly
    - Following years produced faster, better, cheaper models.



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Application

Overhead Imagery

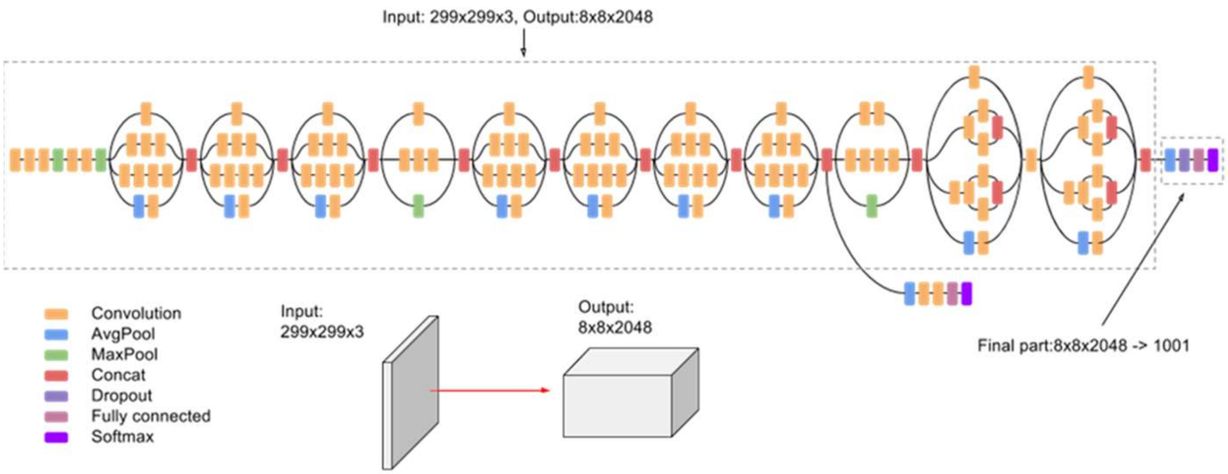
- Aerial
  - Nearmap
  - EagleView
- Satellite
  - Digital Globe
  - Landsat
  - Sentinal 2
- Drone
  - DroneBase
  - Measure

- Terminology
  - GSD – ground sample distance
    - Distance between pixel centers on the ground
  - Geo-referenced
    - Each pixel is associated with a point on the ground
  - GIS - Geographic information systems
    - Software capable of doing geographic computation and storage
  - Color – specific wavelength(s) of light
    - We see red, green, blue, but there are others such as near-infrared, ultraviolet.

Labeling

- Deep learning requires a lot of label data
- First try – agent entered data
  - Human curated
  - Widely available
  - Poor accuracy for several roof types
  - Garbage in, garbage out
- Second try –real estate listings
  - Human curated
  - Widely available
  - High accuracy for expensive roof types

Model



- Deep learning model
- Common off-the-shelf architectures
  - Establish baseline
  - Well understood
  - Easier to train and optimize
  - Take advantage of transfer learning i.e. pre-trained models
  - Available for all major libraries

https://cloud.google.com/tpu/docs/inception-v3-advanced

Experiment

- Overhead imagery
  - 3 inch GSD
    - 100's TB
    - Expensive
    - RGB
  - 1 m GSD
    - 10's TB
    - Cheap
    - Multi-spectral
- GIS data
  - Parcel boundaries
  - Building footprints

USGS Public Domain

Experiment

- Carrier Test Set
  - Inspected records
- Performance
  - 3" – 9% absolute improvement over baseline
  - 1 m – 7% absolute improvement over baseline

USGS Public Domain

Try It At Home

- Google Colab – a free python notebook environment hosted by Google. Now with GPU and TPU!
- Iris example:
- https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/eager/custom_training_walkthrough.ipynb
- Deep learning etc. examples
- https://github.com/Hvass-Labs/TensorFlow-Tutorials

Machine Learning & Roof Condition

Leverage growing sophistication of multiple roof data assets

Create a single, comprehensive roof intelligence solution

- FL study with roof condition proxy and carrier claims data
- Nationwide study with carrier inspection results

Speaker: Tanya Havlicek

Roof Condition & Data Asset Exploration Tampa Bay, FL

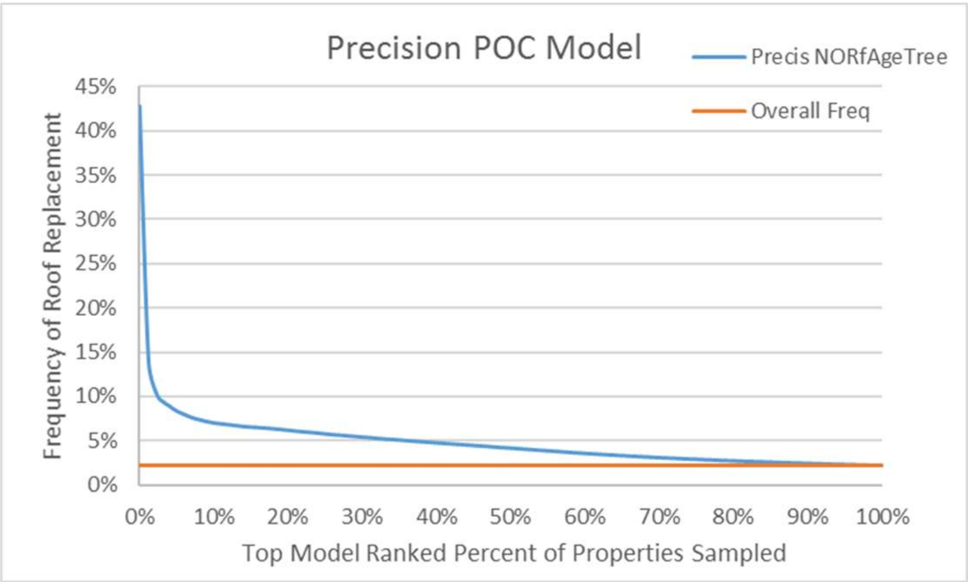
Comprehensive Score with Proxy POC FL 3 County

- Data Pull:
  - Predictive: Property Characteristics, Forensic Hail, Climate, Hazard Risk Layers, ZIP Code Demographics
  - Target: Roof materials Receipts: Assume poor condition requiring repair (proxy for poor condition)

Data Asset	Level	Examples Include
Property Characteristics	Property	Square Feet, Year Built, Exterior Wall, # Bathroom, etc.
Roof Characteristics	Property	Material, etc.
Weather related events	Property	Historical Hail, Wind, Precipitation, etc. *Upcoming* CAPE Hail prediction/risk score
Hazard and Geospatial layers	Property	Hurricane, Storm Surge, Flood, Earthquake, Fire Response, Coastal Distance, etc. **RISK SCORE**
Area Demographics	Zip Code	Income, Age, Population Density, etc.
Climate Data	Zip Code	Wind Speed, Max/Min/Average Temperature, Relative Humidity, etc. **LONG TERM**

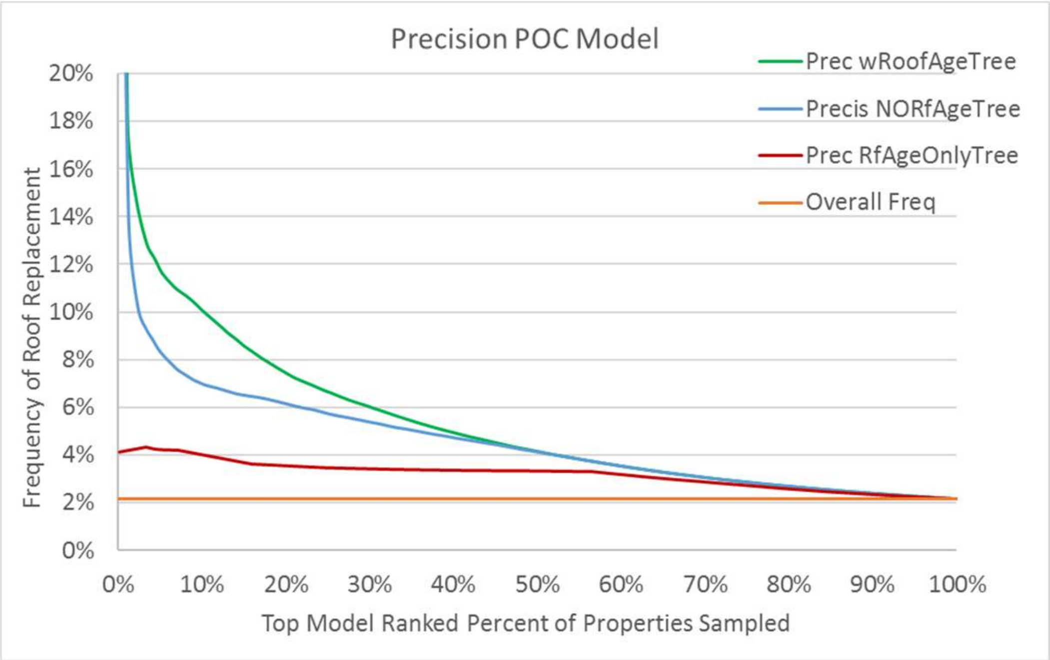
Model Performance Cross Validation (Excl Roof Age)

- Three counties in FL: Hillsborough, Manatee, Pinellas
- ~890,000 properties
- ~19,000 Roof Contractor Receipts (2% overall)
- 1/1/2011 through 12/31/2015 (5 years)



- Precision = the percent roof replacement on properties sampled by model rank
- Top 1% of properties (based on highest score) have 43% roof replacement (1888% lift)
- Top 20% of properties have 6% roof replacement (185% lift)

Model Performance Add Roof Age

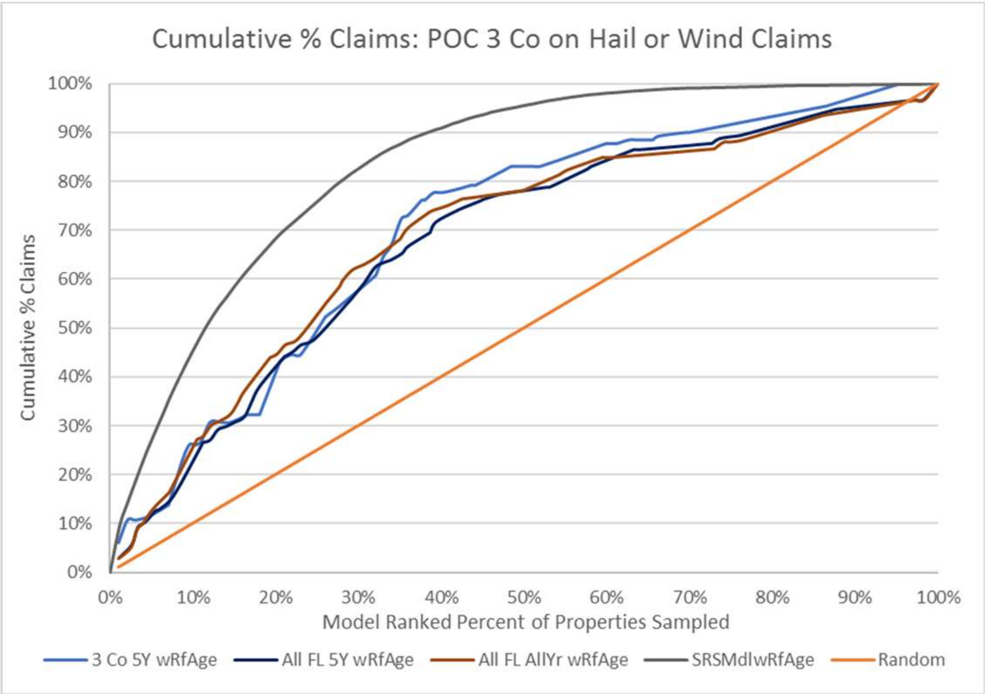


More than Roof Age is important!

- **Precision** = the percent roof replacement on properties sampled by model rank
- **Lift** = Scaled Precision: Percent roof replacement at percentile divided by overall frequency
- **Top 10%** of properties (based on highest score) show **precision**
  - 10% (Model CLGX assets and Roof Age) (366% lift)
  - 7% (Model CLGX assets only) (222% lift)
  - 4% (Model Roof Age only) (77% lift)

Precision At Ranked Top 10%:
Adding Roof Age improves CLGX model 3 ppt, ↑1.4x
Adding CLGX improves Roof Age Only model 6 ppt, ↑ 2.5x

Model Performance on claims data



- **Top 10%** of properties (based on highest score) capture
  - 27% of claims when applied to entire state of FL 5 years exposure
  - 18% of claims when applied to entire state of FL all years exposure
  - 26% of claims applied to 3Co5Y
- **Top 30%** of properties (based on highest score) capture
  - 60% of claims when applied to entire state of FL 5 years exposure
  - 57% of claims when applied to entire state of FL all years exposure
  - 61% of claims applied to 3Co5Y

Can apply to different carrier policy set definitions

- same as model build (3 Co 5 Years)
- All of FL 5 Years
- All of FL all years (Jan 2010 +)

Roof Condition & Data Asset Exploration National Carrier

Comprehensive Score with Carrier

- Data Pull:
  - Property Characteristics Pre-Inspection, Forensic Hail, Climate, Hazard Risk Layers, ZIP Code Demographics
  - Modeled Reconstruction Cost, Post-Inspection property data
  - Targets: Major Roof Issue identified from inspection with and without policy cancellation
  - Initial Imagery modeled roof characteristics

- Exploratory data analysis
  - Data time frame: Inspections 2009 – present available, focus on 2015 to Jun 2018
  - Volumes: >30K inspections Jan 2015 to Jun 2018 selected
  - Variable characteristics (200+ variables)
  - Inspection outcome review
  - Relations between Inspection results and characteristics

Roof Material

Characteristic	Distribution
Missing	40.0%
Asphalt	25.0%
Composition Shingle	24.6%
Tile, Concrete	2.4%
Other	1.4%
Tile	1.3%
Built-up Tar and Gravel	1.2%
Metal	1.1%
Rubber	0.7%
Shake	0.5%
Fiberglass	0.3%
Tile, Clay	0.3%
Slate	0.3%
Roll Composition	0.2%
Wood Shingle	0.2%
Asbestos	0.2%
Enamel	0.1%
Roll Paper	0.1%
Steel	0.1%
Aluminum	0.1%
Synthetic	0.0%

Tabular data at the property address level

~60M addresses in the United States

available pre-inspection

Asset Compare Post vs Pre Inspection Roof Material

New Inspections Jan 2015 - Jun 2018

Asset Comparison RCTExpress Inspection versus Pre-Inspect Primary Roof Material (Rank Ordered)	Not Null Match InterChg	Not Null NotMatch InterChg	Null InterChg
SHINGLES ASPHALT FIBERGLASS	96%	4%	55%
SHINGLES ARCHITECTURAL	93%	7%	61%
TILE CONCRETE	93%	7%	43%
STEEL STANDING SEAM	6%	94%	77%
STEEL	45%	55%	75%
BUILT-UP TAR AND GRAVEL	72%	28%	74%
TILE CLAY	38%	62%	49%
ROLLED ROOF SINGLE PLY	7%	93%	76%
RUBBER	6%	94%	71%
SHINGLES ASPHALTFIBERGLASS IRR	97%	3%	58%
SLATE	67%	33%	66%
SHAKES WOOD	40%	60%	62%
ALUMINUM STANDING SEAM	0%	100%	68%
SHINGLES WOOD	0%	100%	75%
ALUMINUM CORRUGATED	0%	100%	75%
TIN	11%	89%	81%
SHINGLES STEEL	0%	100%	74%
FOAM	8%	92%	29%
TILE SPANISH	78%	22%	64%
SHINGLES ALUMINUM	50%	50%	76%
SHINGLE CEMENT FIBER	40%	60%	67%
SHINGLES STEEL AGGREGATE FINISH	0%	100%	60%
All Other	58%	42%	77%
Total	90%	10%	59%

Asphalt fiberglass shingles: Most Frequent

- 96% match when IC populated (Null 55%)

Architectural shingles: 2nd Most Frequent

- 93% match when IC populated (Null 61%)
  - ~30M addresses with Pre-Inspection value
  - Spot checks show inspection roof images agree to inspection result when sources mismatch
  - Some mismatching may be due to different material naming conventions between systems

Asset Compare Pre vs Post Inspection Roof Material

New Inspections Jan 2015 - Jun 2018 Asset Comparison Pre-Inspect versus RCTExpress Inspection Primary Roof Material (Rank Ordered)	Not Null Match	Not Null Not Match
Asphalt	98%	2%
Composition Shingle	98%	2%
Tile, Concrete	81%	19%
Other	0%	100%
Built-up Tar and Gravel	24%	76%
Metal	34%	66%
Tile	84%	16%
Rubber	0%	100%
Slate	57%	43%
Shake	32%	68%
Fiberglass	43%	57%
Enamel	0%	100%
Asbestos	0%	100%
Wood Shingle	0%	100%
Tile, Clay	44%	56%
Roll Composition	10%	90%
Roll Paper	0%	100%
Steel	57%	43%
Aluminum	0%	100%
Total	90%	10%

Asphalt : Most Frequent

- 98% match

Composition shingle: 2nd Most Frequent

- 93% match

Tile, Concrete: 3rd Most Frequent

- 81% match

Some mismatching may be due to different material naming conventions between RCTExpress and InterChange

Comprehensive Roof Intelligence Score

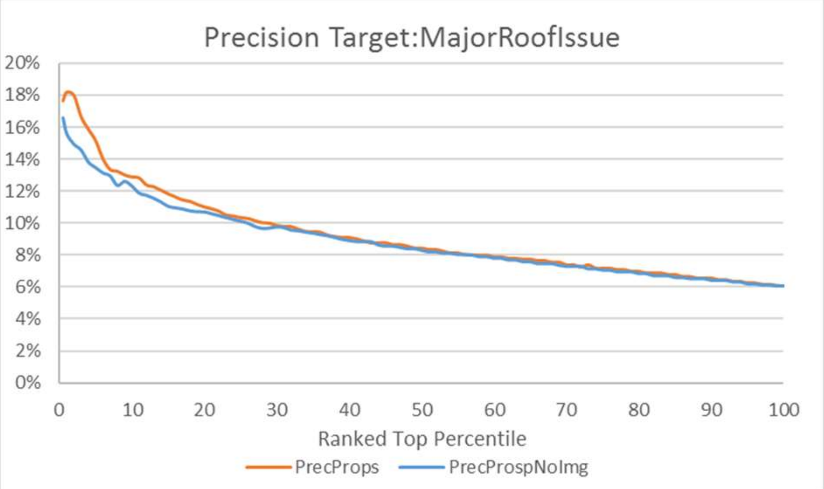
“Prospective” Random Forest Model (Pre-Inspection Independent Var’s)

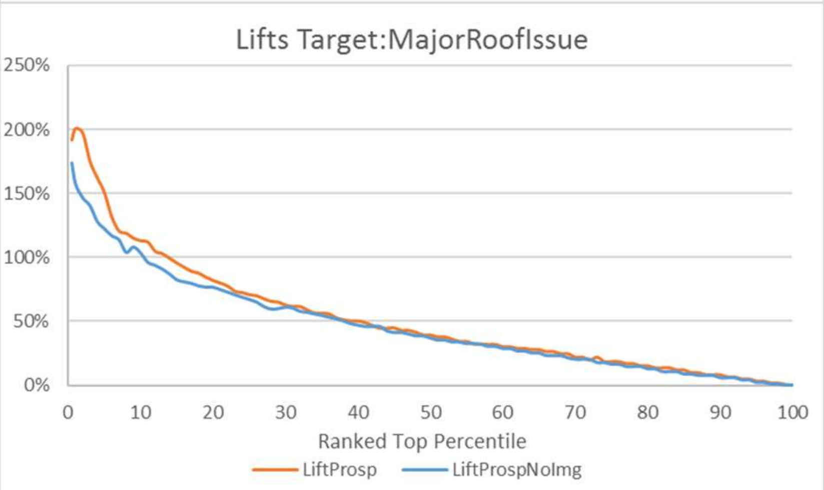
- Dependent Target Variable:
  - Inspection Result:
    - Major Roof Issue
    - Policy Cancellation with Major Roof Issue
- 148 Independent Variables: Use only those available prior to Inspection
  - CLGX (Modeled Reconstruction Cost, Total Living Area, Year Built, Number of Stories, Roof Material, Roof Age, Exterior Wall, etc)
  - <u>Imagery Modeled Roof</u> (slate, flat, asphalt, wood, tile, metal)
  - Natural Hazard Risk (Long term: Hail, Hurricane Wind, Straight Line Wind, Tornado, Wildfire, etc)
  - Climate/Weather by ZIP (Avg Annual Rainfall, Max/Min monthly temperature, Avg Hourly Wind Speed, etc)
  - Historical Hail by size at location and within 1 mile in last 3, 6, 12, 24, 48 months
  - Demographics by ZIP (population growth, median household income, etc)

Comprehensive Roof Intelligence Score

Prospective Random Forest Model

- ***On top of algorithm already in place -- inspections***
- Orange line includes Imagery modeled roof type and Interchange roof material
  - Imagery Does improve lift
  - Replacing tabular with image yields similar results
- Lift = (Precision in percentile / Overall precision – 1)%
- Precision = Targets/Inspections aka Rate
- Top 10th percentile has 113% lift
  - 12.88% precision in percentile versus 6.05% overall
  - (12.88/6.05-1)=113%
  - Rate of Major Roof Issue is 2.13 times higher in the model ranked top 10th percentile than overall inspections (12.88% vs 6.05%)

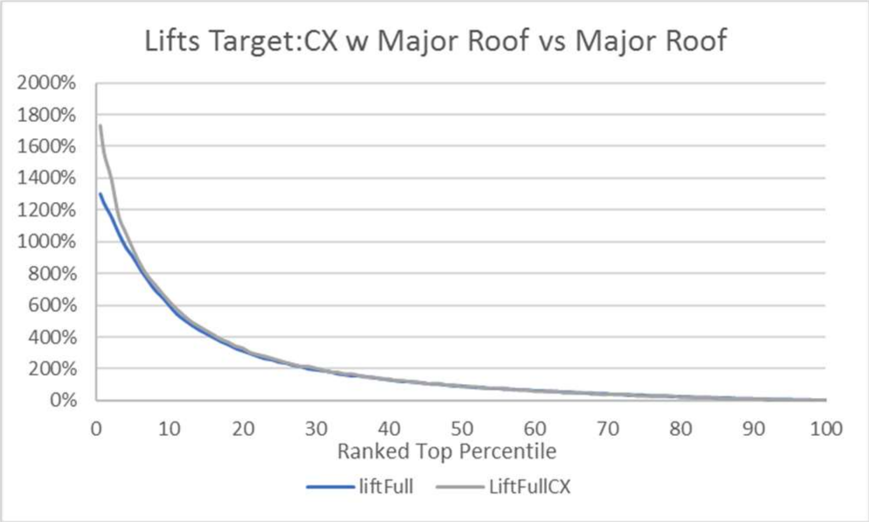




Comprehensive Roof Intelligence Score

Full Random Forest Model

- ***On top of algorithm already in place -- inspections***
- Dependent Target Variable:
  - Inspection Result:
    - Major Roof Issue
    - Policy Cancellation with Major Roof Issue
- 376 Independent Variables:
  - Use all variables in Prospective Model (those available prior to Inspection)
  - PLUS all inspection data Including the RCTExpress Form variables potentially roof relevant (Roof material detail, Roof Life Remaining, Roof Shape, Reconstruction Costs by System/Parts/Labor/Equipment, etc)
  - Excluded Imagery because boots on the ground inspection data used



Comprehensive Roof Intelligence Score

Major Roof Issue Variable Importance Top 10 Compare Prospective vs Full

- Gini Importance or Mean Decrease in Impurity (MDI) calculates each feature importance as the sum over the number of splits (across all trees) that include the feature, proportionally to the number of samples it splits

VarRankImp	ProspMajorRoofWithImg	FullRoofMajor
1	RoofAge	RoofLifeRemain
2	ElevAspectAzimuth	ROOF_SHINGLES_ASPHALT_FIBERGLASS
3	GeoLon	GeoLon
4	FRSDistHundredYrFloodPlainFt	Roofing_Material_Cost
5	FRSElevationVarianceFt	RoofAge
6	GeoLat	GeoLat
7	RCT	MainWallHt9Pct
8	tile	MainYEARBUILT
9	wood	Roofing_Total_Cost
10	slate	SUP_YEARBUILT

Thank you!