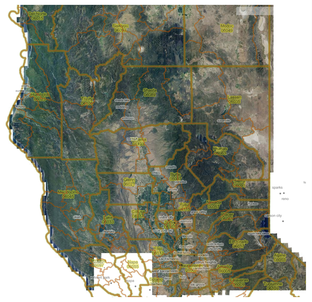
OBIA

Object-Based Image Analysis for buildings extraction in California

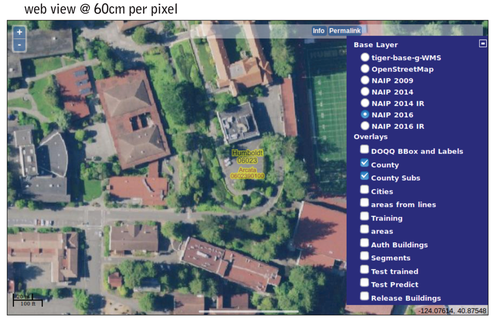
NAIP

National Agricultural Imagery Program 2016



USGS Imagery Programs supplied 2016 **DOQQ** "digital orthophoto quadrangle" for California as 11,000 GeoTIFFs in four-bands; aprox. 5TB on disk.

web view @ 60cm per pixel



NAIP quad (DOQQ) is processed into multiple products for analysis

layer mode	description
tc	true color (r,g,b); JPEG in GeoTIFF; YCbCr
fc	false color (ir,g,b)
ir	infrared
5b	Sobel filter, mask, ir, fc, tc

Synthetic Layers

Berkeley ImageSEG 2

BIS2

Berkeley ImageSEG • C library

A segmentation kernel with library routines which take raster GeoTIFF or GDAL VRT and produce polygons with statistics, called segments.

parameters

t	threshhold
s	shape count
c	compactness

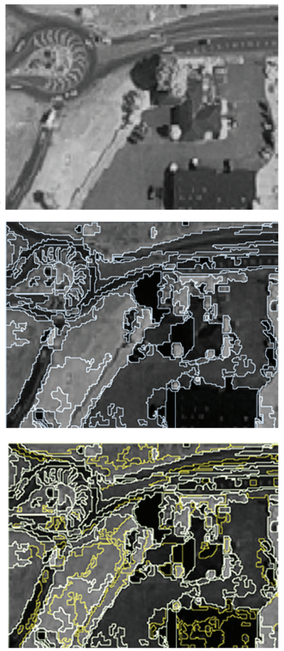
BIS2 Segmentation Kernel Output Examples

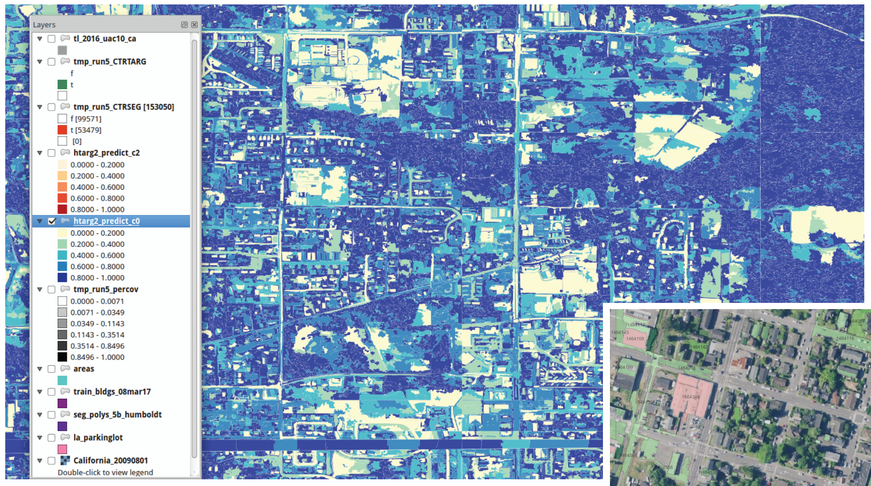
b.0) sample NAIP imagery

b.1) segmented results using a low threshhold (t) value

b.2) vary only (t) to a higher value; notice the same polygon boundaries return in addition to new interior polygons.

BIS2 Segmentation

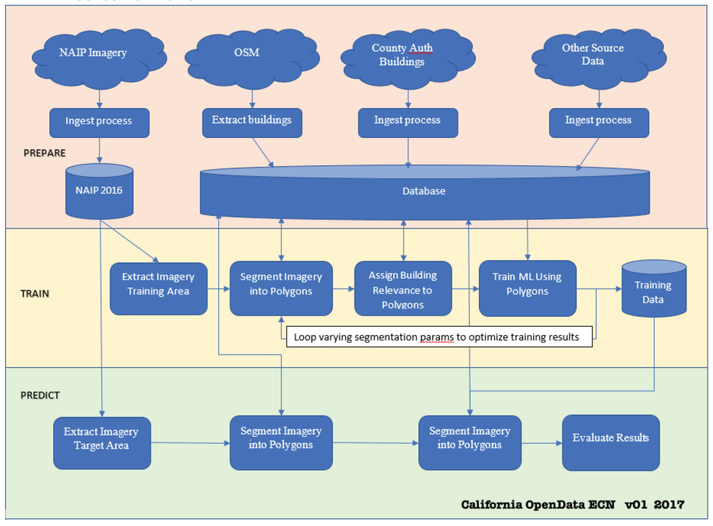


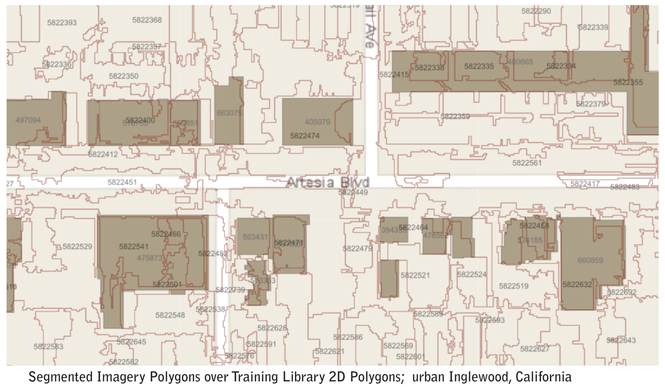


Imagery Segmented, Classified and Predicted as 2D Polygons; Arcata, California

NAIP imagery in a search area is segmented. Classification is performed via Scikit-Learn GBT. A Gradient-Boost Tree (GBT) model is saved in the training phase, and applied to new areas. Defined **classes** are: **0** not a building; **2** commercial building of interest; **1** other building Each polygon gets three attributes [0 - 1.0] as the probability of class identity e.g. **htarg2_predict_c0**. Zero means not at all likely, 1.0 means certainty; in practice, the three together equal 1.0.

Data Processing Flows





Segmented Imagery Polygons over Training Library 2D Polygons; urban Inglewood, California

NAIP imagey is processed via BIS2 library emitting polygon geometry plus statistics per polygon. Unique ID (pkey) for both segment polygons and training polygons are labeled.

Overview, or How to Read this Poster

NAIP Raster Inputs are Split into Layers

- synthetic layers are then produced and stored

Openlayers web defines machine-addressable layer navigation via URL

BIS2 Kernel Produces Segmentation Polygons

segments vary substantially by parameter, so try many variations
Use efficient methods to search & sort the segment results; pick a winner

Create a Library of Search Targets

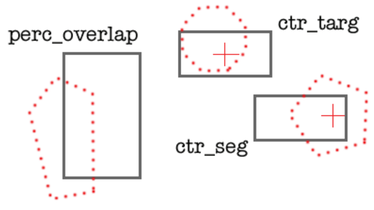
use authoritative 2D polygons plus attributes for buildings of interest
match building type classifications in a 'crosswalk'

Scikit-Learn Engine to Train, then Search

segments over search targets are scored into defined classes
Apply segmentation to a new search area; match with training model; show results

Segment Polygon Relevance Tests

Each step of the pipeline uses database tables to store its result. Subsequent steps read tables as input. Here, segmentation result polygons are tested against reference polygons to compute measures of similarity. Database schema `relevance` gets a **Five Tests** result table on all polys in a given segmentation run.




```
insert into relevance."%s"
  select a.gid,
         %d::integer,

 -- pctoverlap
         st_area(st_intersection(a.geom,c.geom))/st_area(a.geom),

 -- coverage1
         (st_area(c.geom) + st_area(a.geom) -
            Z.0*st_area(st_intersection(a.geom,c.geom))) /
            (st_area(c.geom) + st_area(a.geom)),                    COV1

 -- coverage2
         (st_area(c.geom) - st_area(st_intersection(a.geom,c.geom)))
           / st_area(a.geom),                                       COV2

 -- centr_seg
         st_intersects(st_centroid(a.geom), c.geom),

 -- centr_trg
         st_intersects(st_centroid(c.geom), a.geom)


    from %s a                                       -- (a)segment polygons
         join %s c on st_intersects(a.geom, c.geom) -- (c)building polygons

         left outer join relevance."%s" b on a.gid=b.gid
   where b.class is null ''' % ( rtable, clss, table, btable, rtable )
```

Segmentation Trials

In order to choose which segmentation settings best fit per "Segmentation Goodness"[1], each of the three BIS2 params were varied and those permutations were applied. **Five Tests** are applied to every eligible segment polygon and stored in a table named for the run. Note that the number of segments in a result set will vary and are distinguishable fairly easily.

```
   jobid    |  project  | mode | t  | s | c |   cnt
------------+-----------+------+----+---+---+---------
 5bandt1    | test2     | 5b   | 50 | 3 | 3 |    3665
 5bandt1    | test2     | 5b   | 50 | 3 | 4 |    3586
 5bandt1    | test2     | 5b   | 50 | 3 | 5 |    3625
 5bandt1    | test2     | 5b   | 50 | 3 | 6 |    3600
 5bandt1    | test2     | 5b   | 50 | 3 | 7 |    3618
 ...
 evaltest   | evaltest1 | tc   | 90 | 9 | 3 |     342
 evaltest   | evaltest1 | tc   | 90 | 9 | 5 |     387
 evaltest   | evaltest1 | tc   | 90 | 9 | 7 |     397
 evaltest   | evaltest1 | tc   | 90 | 9 | 9 |     421
 ...
 humboldt   | target2   | 5b   | 50 | 3 | 3 | 330852
 inglewood  | run2      | 5b   | 50 | 3 | 3 | 228747

(828 rows)
```

A single SQL statement evaluates summary statistics on some number of tables of interest to pick a winner. For example, for all matches on a (jobid,project) pair, any (s,c) with (t) less than 100, find the median value of column **cov1** for each table, then sort them and select the closest to (1.0). A python function generates SQL, and another executes it synchronously.

[1] **Accuracy Assessment Measures for Object-based Image Segmentation Goodness** Nicholas Clinton, Ashley Holt, James Scarborough, Li Yan, and Peng Gong 2010

Training library polygons in Inglewood, CA.

ML Training Library

Supervised Learning with OBIA

Unsupervised machine learning with pixel-based analysis was not chosen as the methodology for this project. Instead, a newer methodology was chosen, supervised classification with Object-Based Image Analysis (OBIA).

In a supervised classification system with OBIA, representative samples for each class of interest are selected as polygons with attributes, and supplied as inputs to create a training set. In search, Scikit-Learn uses its saved training set to compare new segmented polygons derived from search imagery, and emits a scored likelyhood of class membership for each polygon.

Building the Training Library

1) hand-pick several dozen buildings of interest along with convenient attributes, including a 2D polygon footprint and street address.

2) gather similar records from a very large authoritative set.

3) execute and store **Five Tests** on the intersection of segmented imagery, and all buildings in the training area, and buildings occurring in the training set. The five attributes are stored for every segment in a table, named in such a way as the segementation parameters are visible in the table name.

relevance table (schema.table_name) :

```
relevance.inglewood_run2_5b_50_03_03
  gid integer PRIMARY KEY,
    class integer,
    pctoverlap double precision,
    coverage1 double precision,
    coverage2 double precision,
    centr_seg boolean,
    centr_trg boolean
```


```
# Training Set Text File
#/osmb(zoom level)
  BldgTypeID, BldgTypeName,
    Rooftype, Context, Desc
  ...
#14. Hawthorne Elementary School
/osmb/?zoom=18&
  lat=40.80213&lon=-124.16604&
  layers=00000B0TTFFFFF
47  Non-Urban Elementary School
  White corrugated metal
  Asphalt playgrounds & parking lots,
  fields, suburban cul-de-sac neighborhood,
  citrus orchards
    Riverside, CA

Building Types Crosswalk
  ...
13,Commercial,Department Stores,39,,1
14,Commercial,Supermarkets,41,,1
  ...
16,Commercial,Shopping Centers (Regional),39,,1
17,Commercial,Office Buildings,32,,1
```

```
sd_data.train_bldgs_08mar17
 gid                | integer
 building_type_id   | integer
 building_type_name | text
 situscity          | text
 shp_area_m         | integer
 geom               | geometry(MultiPolygon,4326)
 ...
```


Brian M Hamlin
Steve Woodbridge
California OpenData ECN
+1 510 225 1702
ECN@light42.com