Gaussian Process Classification for Galaxy Blend Identification

James Buchanan, Michael Schneider, Robert Armstrong,
Amanda Muyskens, Benjamin Priest, Ryan Dana

Jan 24, 2022

LLNL-PRES-XXXXXX
This work was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under contract DE-AC52-07NA27344. Lawrence Livermore National Security, LLC

Lawrence Livermore National Laboratory

Status update

- Last talk in BL WG: April 26
- Since then:

  Accepted by ApJ on Nov 1, published ten days ago

  doi:10.3847/1538-4357/ac35ca

- Today: Review of the finished paper + DESC project proposal

Detection

- Common deblenders – e.g. SCARLET – require an initial detection step on coadds: estimate of how many objects are in a blend, and where those objects are
- Currently, default detection method is to construct footprints and find peaks in those footprints

Detection

- Common deblenders – SCARLET – require an initial detection step on coadds: estimate of how many objects are in a blend, and where those objects are
- Currently, default detection method is to construct footprints and find peaks in those footprints
- Can we do better?
- Looks like the answer is yes, and with a finite amount of time and effort

Detection

- Common deblenders – SCARLET – require an initial detection step on coadds: estimate of how many objects are in a blend, and where those objects are
- Currently, default detection method is to construct footprints and find peaks in those footprints
- Can we do better?
- Looks like the answer is yes, and with a finite amount of time and effort
- Can we do more?
- Answer: Probabilistic detections

Approach

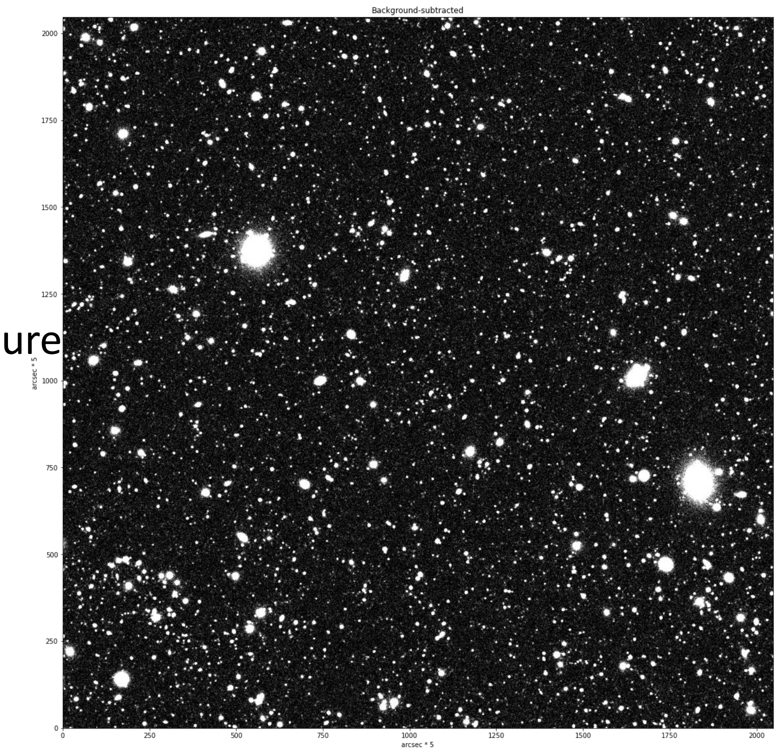
- Get a realistic, astronomically-relevant distribution of blends
- Make footprints
- Test different detection methods on footprints

Galaxy Distribution

- CosmoDC2 galaxy catalog
- Realistic number density of galaxies up through r-band mag 28, and many more up to mag 29
- Used for DESC DC2 campaign

Galaxy scene simulation

- **Sersic model bulge and disk for each galaxy**
  - Sersic parameters, ellipticity components, relative component fluxes from **cosmoDC2 catalog**; overall flux in each band and lensed RA,Dec from DESC **DC2 truth catalog**
- Weak lensing shear and magnification
  - Gamma components and convergence from cosmoDC2 catalog
- Kolmogorov PSF
  - FWHM = 0.7 (+- 10% per exposure)
- Random sub-pixel-scale scene offset (‘dither’) per exposure
- Photon shooting
- Silicon sensor
  - ‘lsst_itl_32’ in galsim
- Sky background
  - Dark sky magnitudes from smtn-002.lsst.io
  - +- 5% mean flux per exposure
  - Poisson noise in each pixel
- **100 separate exposures simulated, then added together**



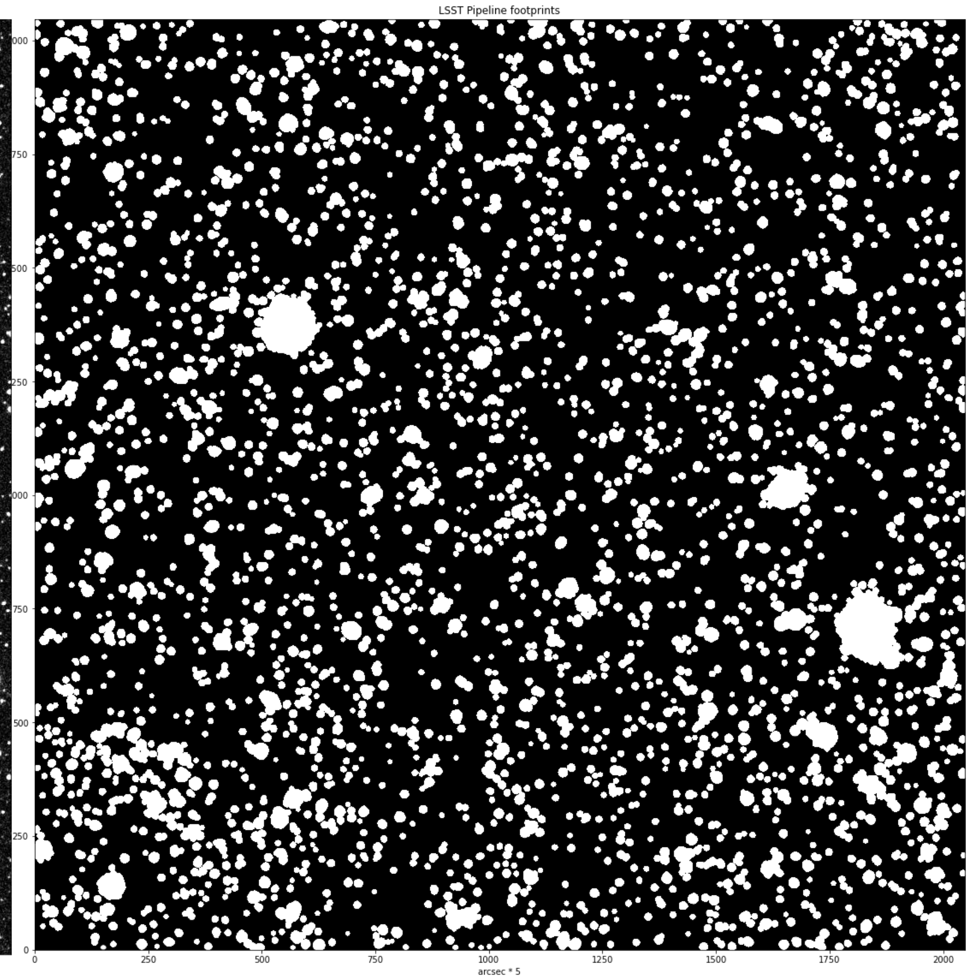
i-band, 2048^2 pixels
(409.6^2 arcsec)

Footprint Construction

- Estimate pixel noise level via clipped variance of coadd pixels
  - Correlated noise correction
- Subtract estimated sky background
- Convolve with Gaussian approximation of PSF
- Threshold each pixel at point-source S/N > 5 to get initial footprints
- Expand these initial footprints by 2.4*PSF width
- Merge any expanded footprints that overlap

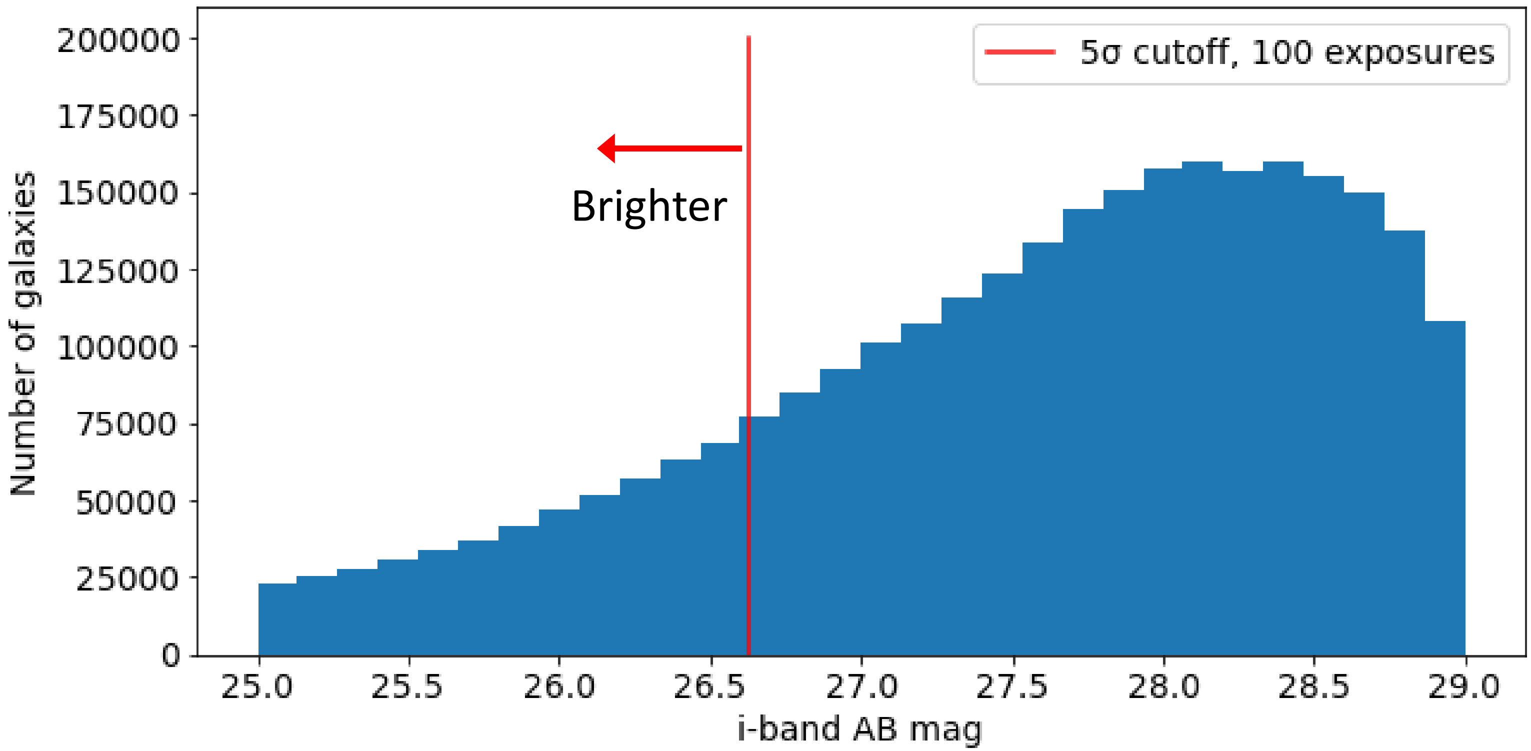
Simulated scene

LSST Pipeline footprints



Dataset

- **Define an i-band footprint as blended** if it contains the center of > 1 galaxy with "significant" (5-sigma) i-band flux



Dataset

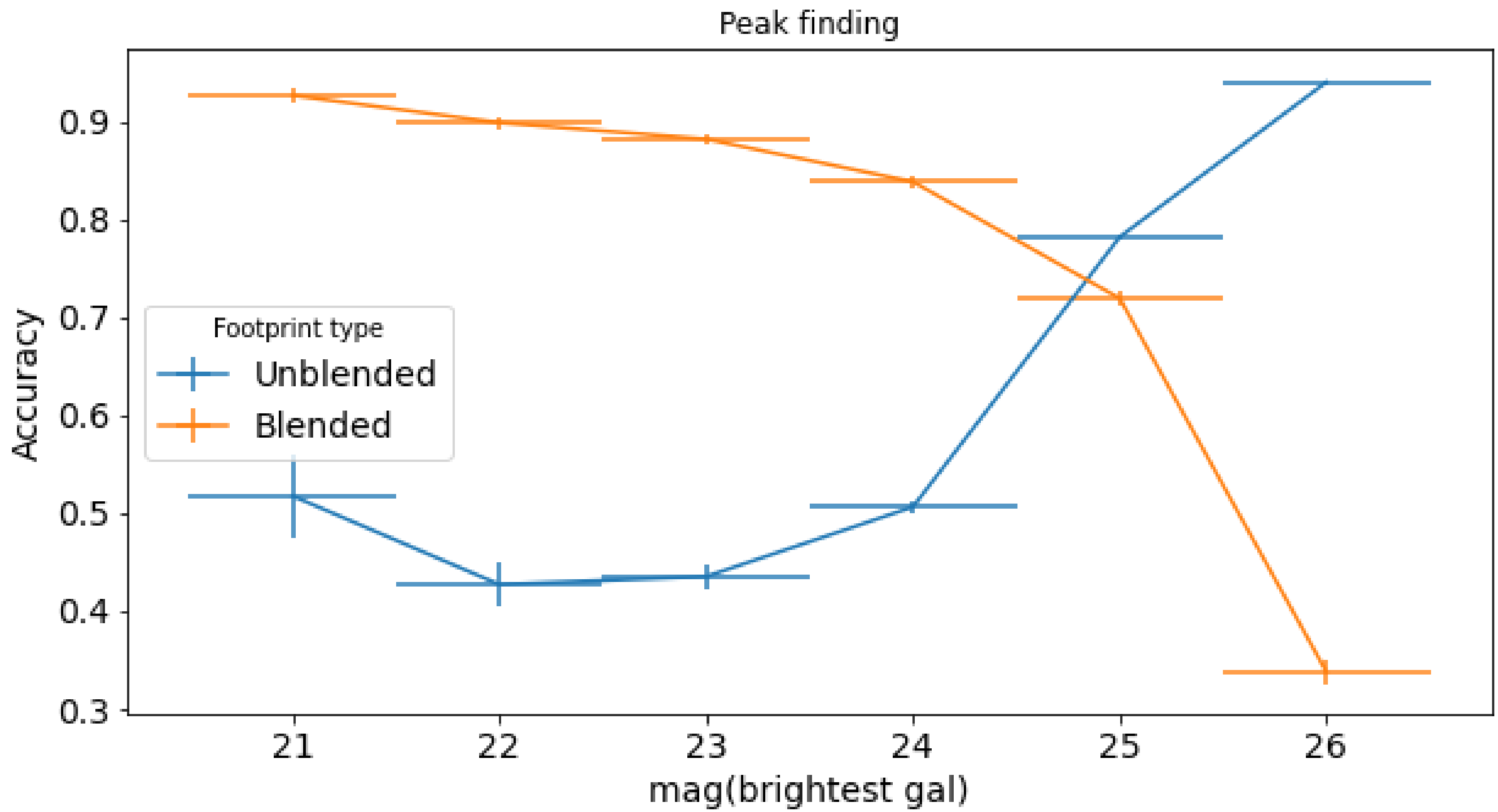
- **Define an i-band footprint as blended** if it contains the center of > 1 galaxy with “significant” (5-sigma) i-band flux

Across 20 total scenes:

- 134,493 total galaxies with i-band flux >= 5 sigma
- 66.01% of these galaxies are contained in i-band footprints
- 0.25% of footprints contain no 5-sigma galaxies
  - Ignoring these here
- 61.74% of footprints are blended
- 38.01% of footprints are unblended

Peak finding

- Overall: Unblended acc**: 0.754,** Blended acc**: 0.789**



Ways forward

- Can we do better?
- Consider other classification models: Logistic regression, CNN, Gaussian processes, …
- Each of these models requires some additional preprocessing of the data
- Each of these models requires a separate training and testing set

Preprocessing

- Select an even mix of blended and unblended footprints for training

For each footprint:

- Make a square **cutout** of a fixed size, centered on that footprint
  - 23 pixels to a side seems to work well
- **Zero out** any pixels that aren't part of the footprint
- **Normalize** pixel values

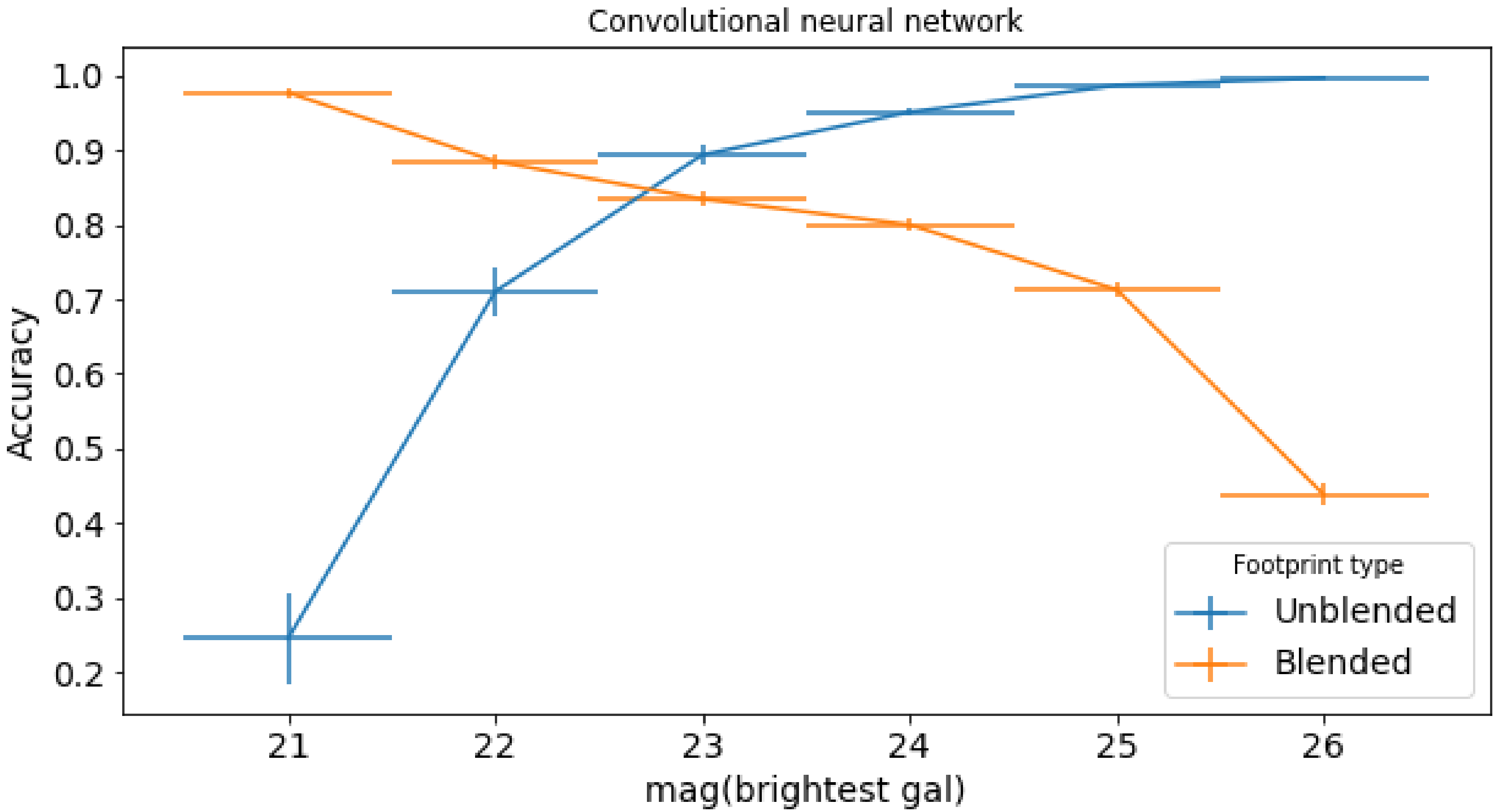
Convolutional neural network: Keras implementation

```
input_shape = (23, 23, 1)
num_classes=2
model = keras.Sequential()

model.add(Conv2D(128, kernel_size=(3, 3), activation="relu"))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, kernel_size=(3, 3), activation="relu"))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(800,activation = 'relu'))
model.add(Dropout(0.2))
model.add(Dense(400,activation = 'relu'))
model.add(Dropout(0.2))
model.add(Dense(200,activation = 'relu'))
model.add(Dense(num_classes, activation="softmax"))
epochs=20
model.compile(loss="binary_crossentropy", optimizer='adam', metrics=["accuracy"])
time_start = time.time()
model.fit(np.reshape(trainxnorm,(len(trainx),23,23,1)), np.array(trainy),
          epochs=15,verbose=True,batch_size=200,validation_split = .1)
train_time = time.time()-time_start
```

Convolutional neural network

- Overall: Unblended acc**: 0.977,** Blended acc**: 0.753**



Preprocessing

- *Select an even mix of blended and unblended footprints for training*

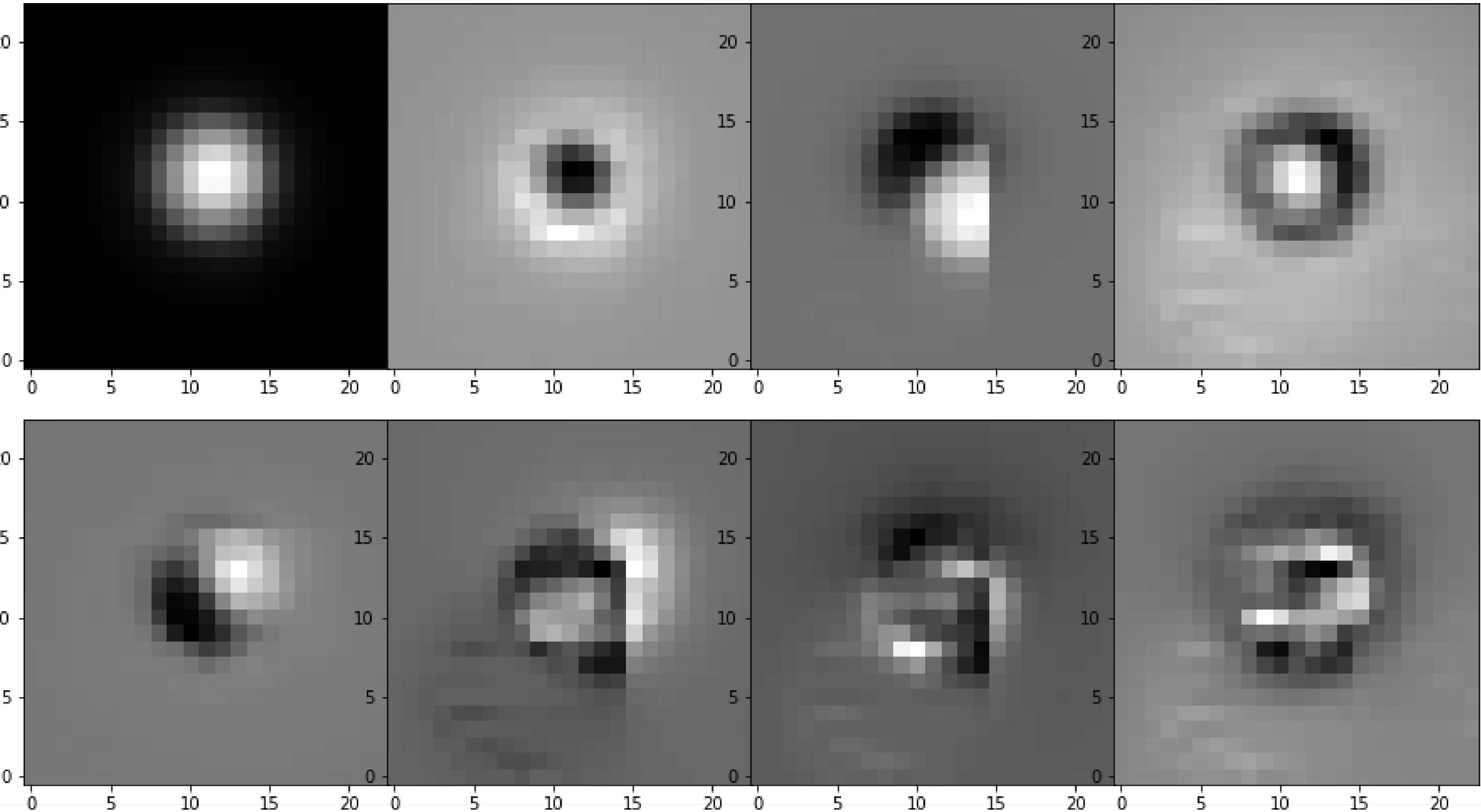
For each footprint:

- *Make a square **cutout** of a fixed size, centered on that footprint*
  - *23 pixels to a side seems to work well*
- ***Zero out** any pixels that aren't part of the footprint*
- ***Normalize** pixel values*

For logistic regression and Gaussian process models:

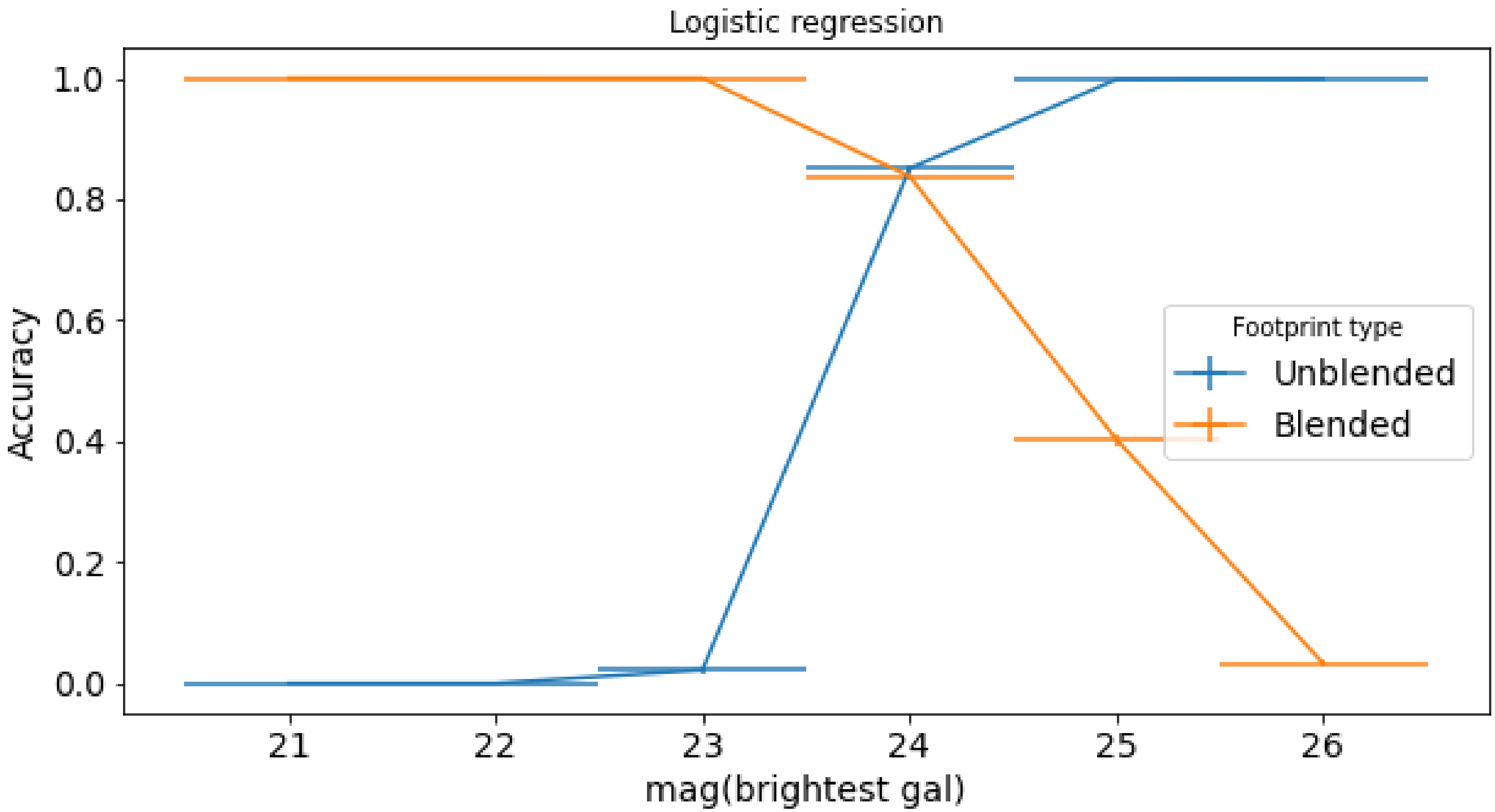
- **Flatten** the 2D pixel array (size=23x23) into a 1D vector (size=529)
- **PCA embedding** to reduce dimensionality: 529 → 8

PCA components
*from an actual DC2 patch



Logistic regression

- Overall: Unblended acc**: 0.895,** Blended acc**: 0.716**



Gaussian Process model

- Gaussian process: An infinite collection of random variables, any finite subset of which is Gaussian-distributed
- The random variables: **For each possible value of the PCA-embedded footprint cutouts, yield a number specifying the "blendedness"**
- For each training example i, define **truth label $\mathbf{y_i}$ = +1 if blended, -1 if unblended**
- Let $\mathbf{f^*}$ denote the **model-estimated blendedness** of test examples
  - If $\mathbf{f^*} > 0$, classify examples as blended; otherwise unblended

Some math

- **Given the PCA encodings of train and test examples,** assert Bayesian **prior** on the joint distribution of **blendedness of training and test sets**:

$$\begin{bmatrix} \mathbf{y} \\ \mathbf{f}_* \end{bmatrix} \sim \mathcal{N}\left(0, \sigma^2 \begin{bmatrix} K_{\mathbf{ff}} + \tau^2 I_n & K_{\mathbf{f}*} \\ K_{*\mathbf{f}} & K_{**} \end{bmatrix}\right)$$

- **Kernel matrices:**

$$(K_{\mathbf{ff}})_{i,j} \equiv k(x_i^{\text{train}}, x_j^{\text{train}})$$
$$(K_{\mathbf{f}*})_{i,j} \equiv k(x_i^{\text{train}}, x_j^{\text{test}}) = (K_{*\mathbf{f}})_{j,i}$$
$$(K_{**})_{i,j} \equiv k(x_i^{\text{test}}, x_j^{\text{test}})$$

- **Matérn kernel:**

$$k_{\text{Matérn}}(\vec{x}, \vec{x}') = \frac{2^{1-\nu}}{\Gamma(\nu)} \left(\sqrt{2\nu}\frac{\|\vec{x} - \vec{x}'\|_2^2}{\ell}\right)^{\nu} K_\nu\left(\sqrt{2\nu}\frac{\|\vec{x} - \vec{x}'\|_2^2}{\ell}\right)$$

More math

- Additionally **given the actual blendedness of the training examples**, we can **analytically compute the posterior** joint distribution of **blendedness of test set**:

$$\mathbf{f}^* | X_{train}, X^*_{test}, y \sim \mathcal{N}(\bar{\mathbf{f}}^*, \sigma^2 C)$$

$$\bar{\mathbf{f}}^* \doteq K_{*\mathbf{f}}(K_{\mathbf{ff}} + \tau^2 I_n)^{-1}\mathbf{y}$$

$$C \doteq K_{**} - K_{*\mathbf{f}}(K_{\mathbf{ff}} + \tau^2 I_n)^{-1} K_{\mathbf{f}*}$$

- Classify test example as blended if $\bar{\mathrm{f}}^*$ > 0

A Note on Training

- CNN and LR models trained to minimize cross-entropy loss

- Gaussian process model trained in two stages:

All hyperparameters other than sigma tuned to maximize balanced accuracy of class label predictions

Then, sigma (which doesn't affect class label predictions) tuned to minimize cross-entropy loss

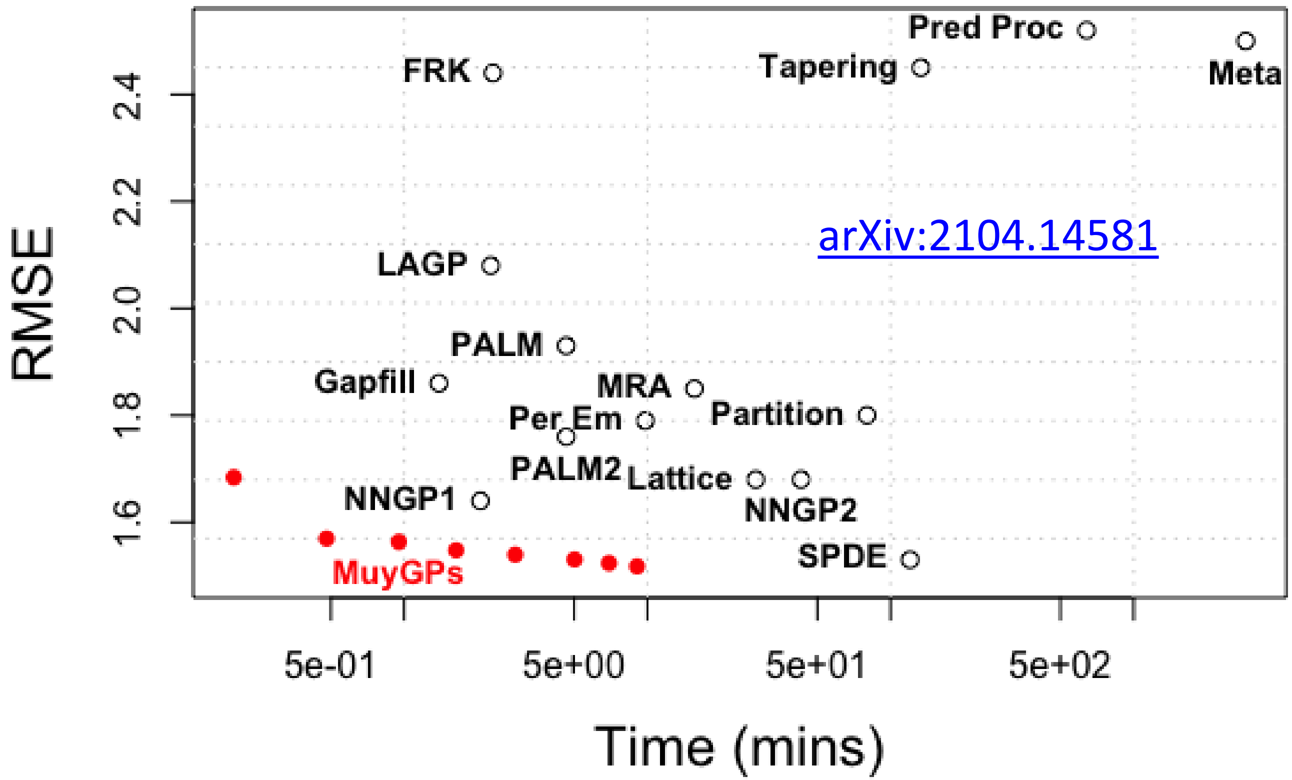
$$\mathbf{f}^* | X_{train}, X^*_{test}, y \sim \mathcal{N}(\bar{\mathbf{f}}^*, \sigma^2 C)$$

$$\bar{\mathbf{f}}^* \doteq K_{*\mathbf{f}}(K_{\mathbf{ff}} + \tau^2 I_n)^{-1}\mathbf{y}$$

$$C \doteq K_{**} - K_{*\mathbf{f}}(K_{\mathbf{ff}} + \tau^2 I_n)^{-1} K_{\mathbf{f}*}$$

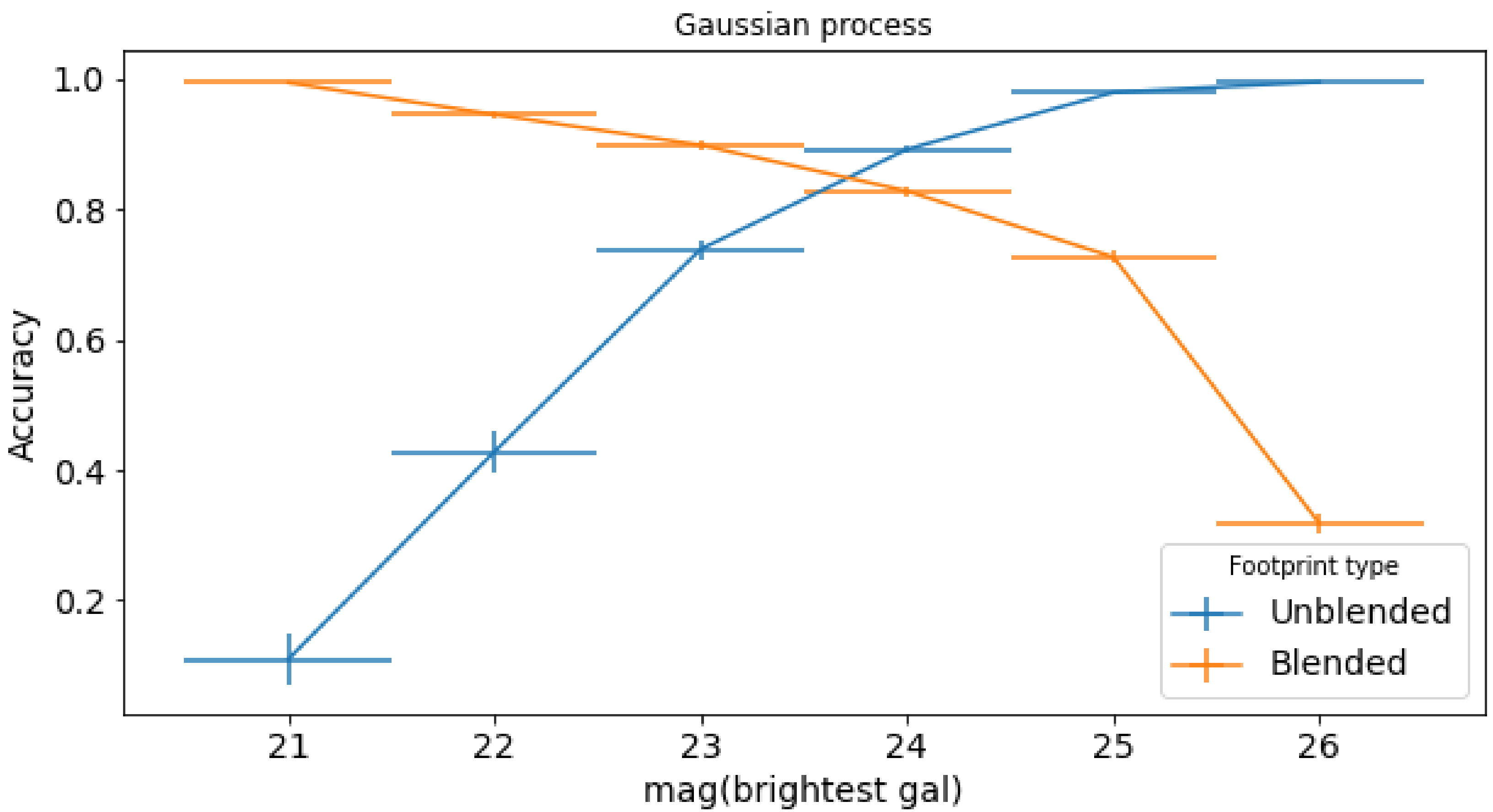
A Note on Speed

- MuyGPs: Very fast implementation of Gaussian process inference + hyperparameter tuning
- https://github.com/LLNL/MuyGPyS



Gaussian process

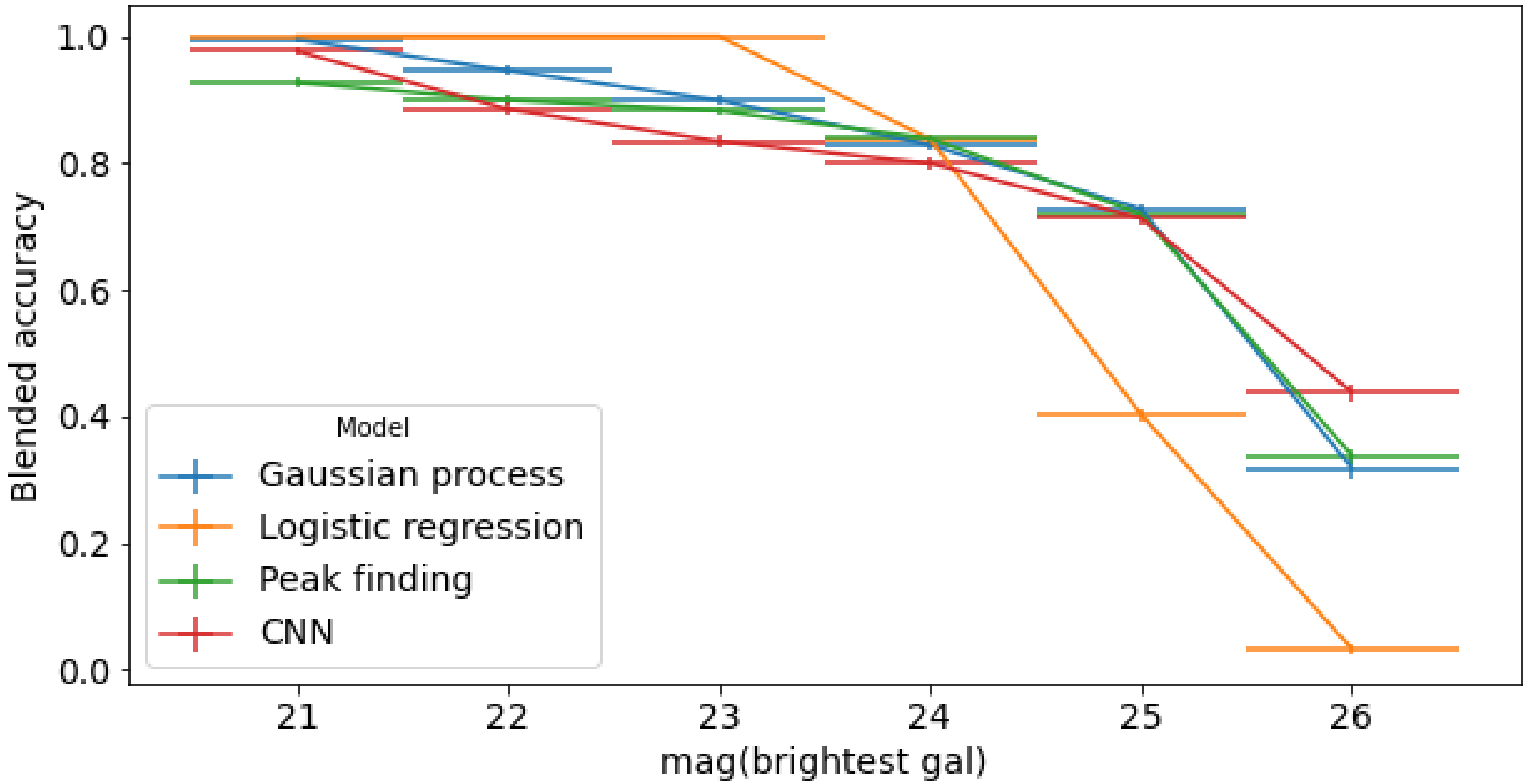
- Overall: Unblended acc**: 0.942,** Blended acc**: 0.800**



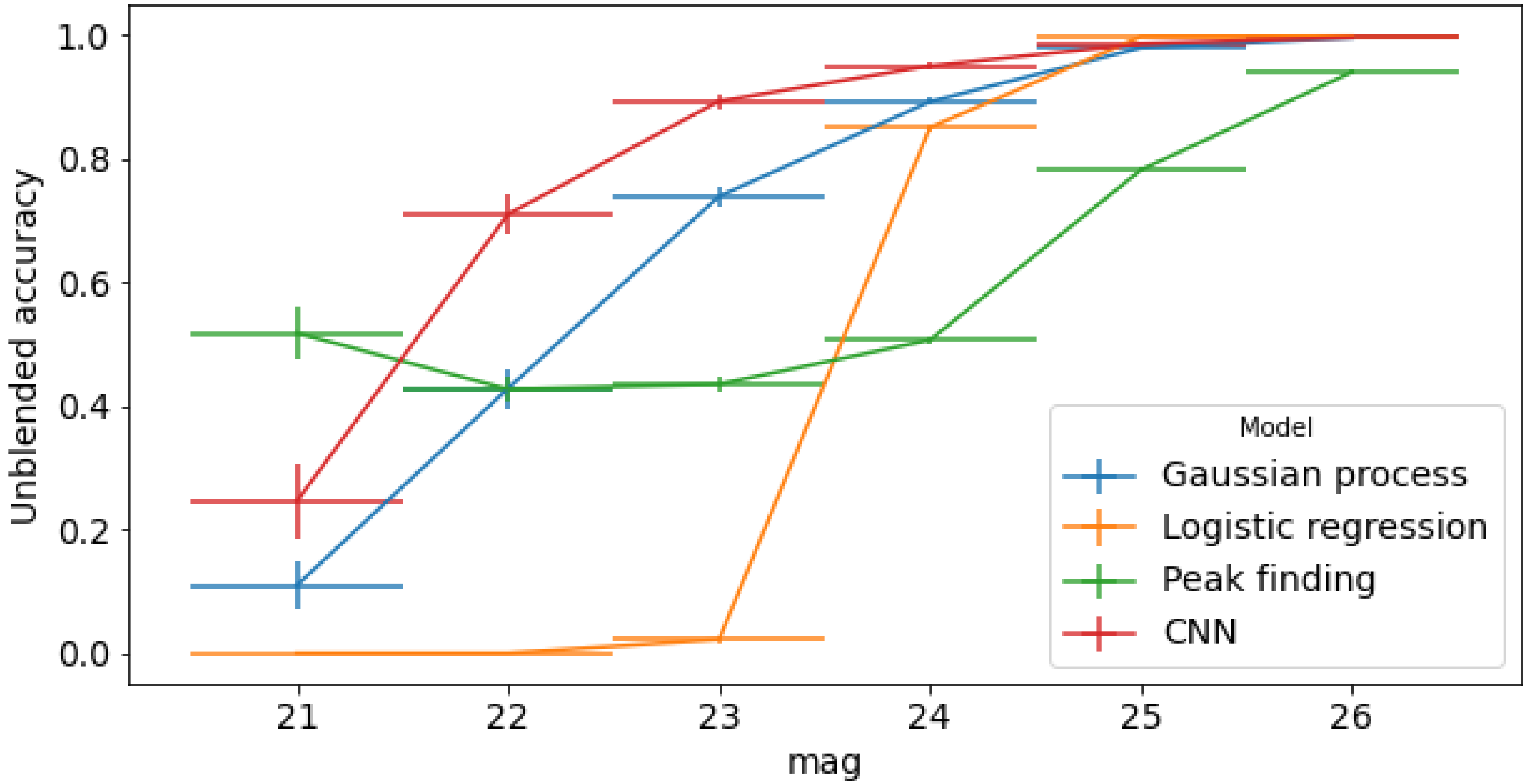
Model Comparison: Overall performance

- **Peak counting**
  - Balanced accuracy = **0.771**
  - Unblended acc**: 0.754,** Blended acc**: 0.789**
- **Logistic regression** with l2 regularization
  - Balanced accuracy = **0.805**
  - Unblended acc**: 0.895,** Blended acc**: 0.716**
- **Convolutional neural network**
  - Balanced accuracy = **0.865**
  - Unblended acc: = **0.977,** Blended acc: **0.753**
- **Gaussian process**
  - Balanced accuracy = **0.871**
  - Unblended acc**: 0.942,** Blended acc**: 0.800**
- Mean cross entropy loss:
  Logistic regression**:** 0.438, CNN: 0.301, Gaussian process**:** 0.324

Model comparison: Blended accuracy

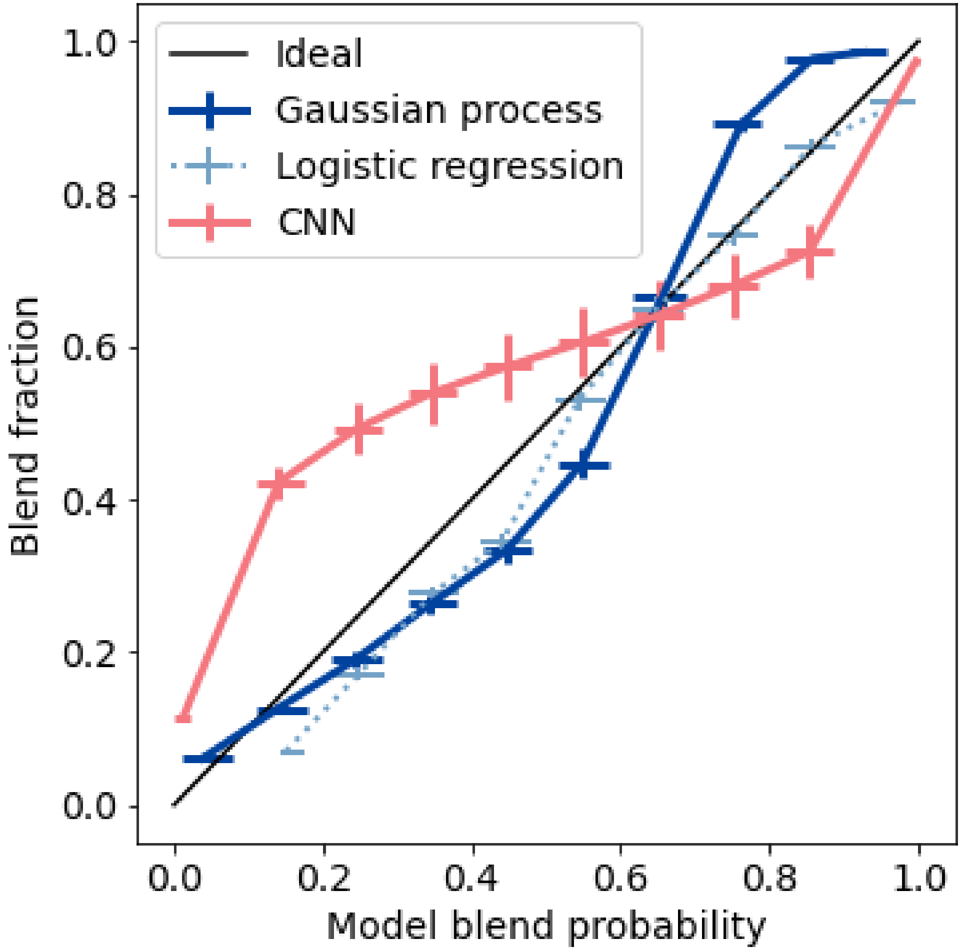


Model comparison: Unblended accuracy



Model comparison: Calibration

- How well can we interpret model score as a blend probability?



Model comparison: Confidence

- How confident are these models when they are right, when they are wrong, and when they disagree with each other?

Cutout	Truth	Peaks	GP	CNN	LR
(a)	Unblended	1	0.052	0.953	0.246
(b)	Blended	1	0.471	0.401	0.255
(c)	Unblended	1	0.510	0.147	0.341
(d)	Blended	1	0.307	0.939	0.346
(e)	Unblended	2	0.283	0.964	0.401
(f)	Blended	4	0.957	7.46e−11	0.974

Some topics for further study: Hierarchical probabilistic detection

- Multi-class classification
  - This work describes a 1 vs. >1 classifier
  - Train additional 2 vs. >2, 3 vs. >3, … classifiers
- Object localization
  - Train a regressor to predict x—y coords of each object
  - Separate regressors for footprints with 1 object, 2, 3, etc.
- If the # of objects and the object locations are all given as probabilities, the combined result is a fully probabilistic detection scheme starting from footprints

Some topics for further study: Include all filter bands

- One option: Build separate classifiers for every band, then later combine results across bands using current Pipelines strategy
- Another option: Concatenate PCA embeddings across all bands, then train model to count the total number of objects that are bright in at least one band

Some topics for further study: Prior mean

- In this study, GP model assumes a prior mean of 0 everywhere, and training set is evenly balanced between blended and unblended examples
- A priori, blend probability actually depends very strongly on footprint size
- Try using a more sophisticated prior mean estimate based on footprint size
- Reassess training set composition

Some topics for further study: Impact on science

- Feed the outputs into a deblender that needs it (SCARLET)
- Check impact on, e.g., weak lensing shear inference

Some topics for further study: Go big

- Test on as much data with as much realism as possible
- DC2
- NERSC

Some topics for further study: Pipelines implementation

- Replace the peak set for each footprint with the GP detection+localization outputs
- Concretely, in findFootprints (afw/detection/FootprintSet.cc), load a trained GP model, and then for every footprint:
  - Ignore the existing call to findPeaks
  - Find instead the model output on that footprint – the number of objects and their locations
  - For each object, call foot.addPeak(x, y, sn)
    - "sn" should be the value at location x, y in the smoothed image
- From this point forward, all references to "peaks" in the Pipelines code actually refer to the GP model outputs
- This works most straightforwardly with the "separate classifier for every band" strategy
- Investigate temporary local background subtraction

Some topics for further study: Model combination

- GP and CNN models seem to make different kinds of mistakes
- Maybe combining the two could cancel out some errors
- This would make the probabilistic interpretation trickier
- The GP model should perform about as well on slightly more realistic data, especially since it's based on a just few PCA components
  - This is true in a preliminary study of actual DC2 images
- But CNN models can suffer sharp performance drop outside training distribution – hard to say how well it would generalize to real images

Some topics for further study: Calibration

- Apply calibration factors to posterior estimates, see if results are more reliable
- Try re-optimizing hyperparameters of calibrated model
  - Re-calibrate, re-optimize, etc.

Some topics for further study: Object definition

- In this study, a footprint is "blended" if it contains more than one "object", and an "object" is defined by S/N > 5 in the i-band
- May be more useful, for deblending, to detect objects down to a lower threshold, even if lower-S/N objects are not kept in a final analysis
- Peak finding can detect arbitrarily low S/N in the outer wings of footprints, down to ~4 in practice
- Preliminary study: GP classifier is about 1% less accurate if S/N > 4 is used
- This also reduces the number of "empty footprints"

Some topics for further study: S/N variability

- In the work above, consistent noise level and PSF width used for each coadd
- In real coadds, these can vary
- These affect S/N calculation, and hence the definition of whether a footprint is "blended"
- Proposed mitigation: Train a separate classifier model for each cell/patch, using the noise level and PSF width estimated in that cell to make training images

Lawrence Livermore National Laboratory