The UoS LAVA group Approach to Generic Image Categoristion

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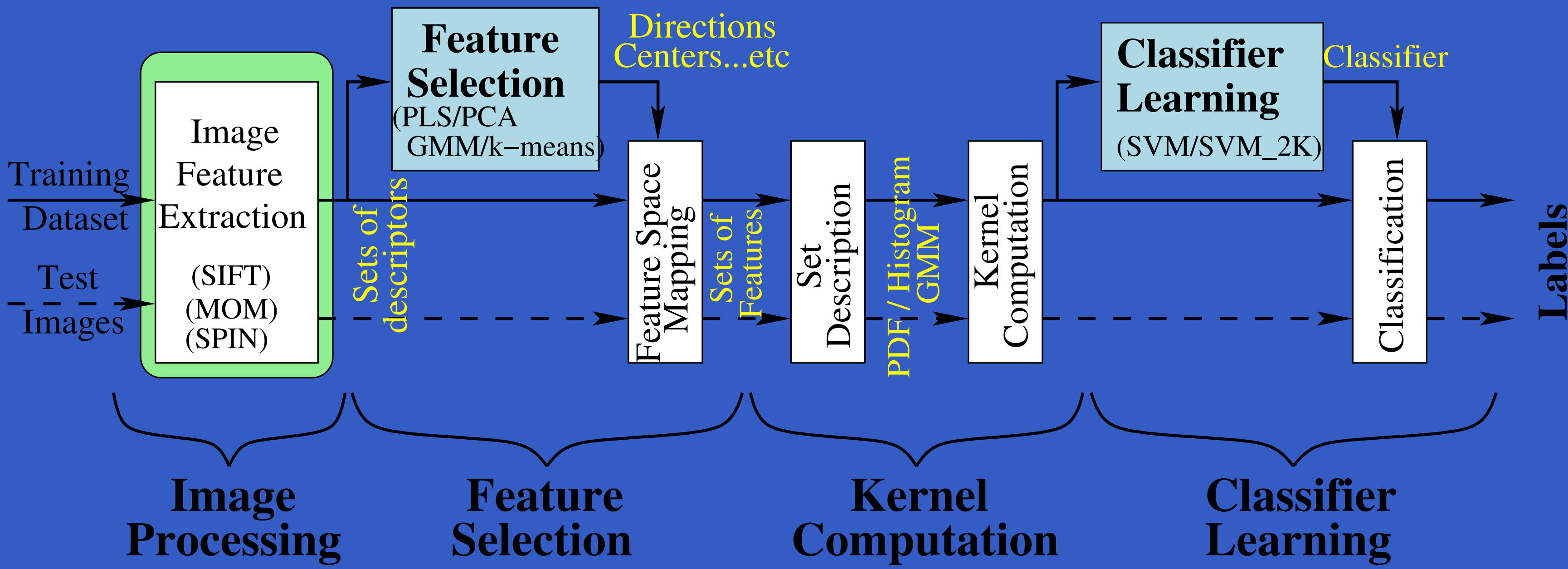
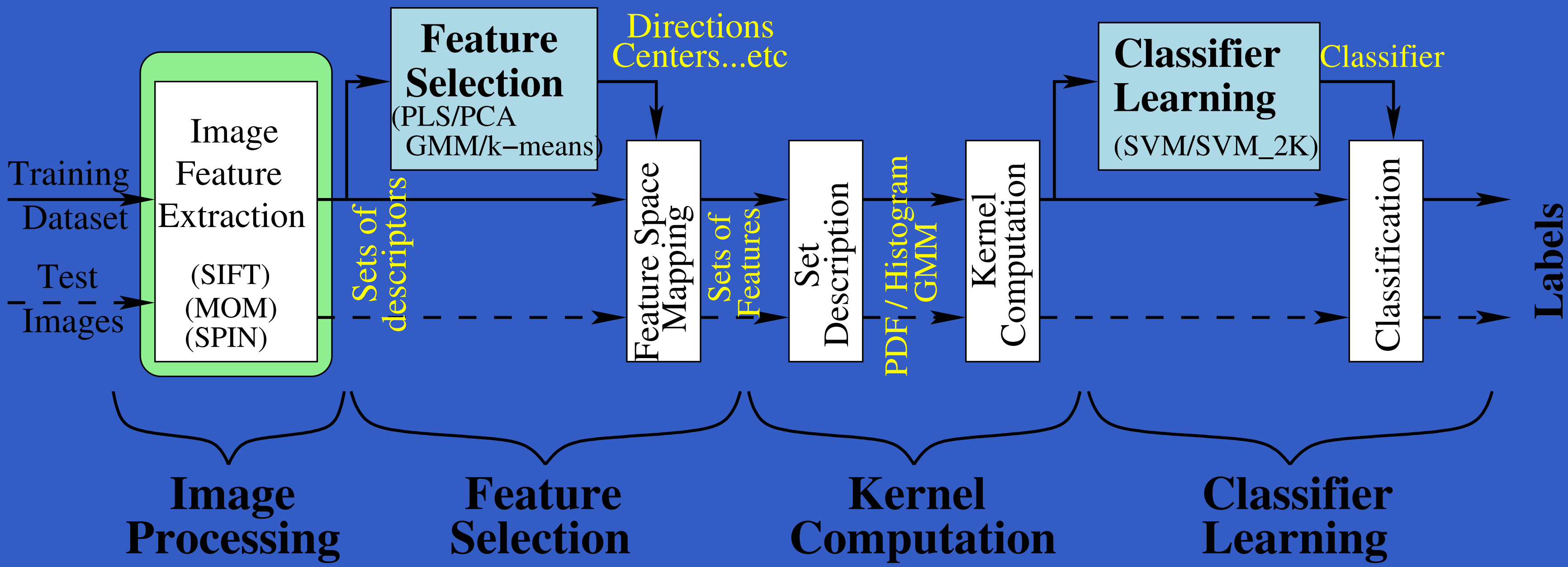
The “set-of-patches” approach to image categorisation.



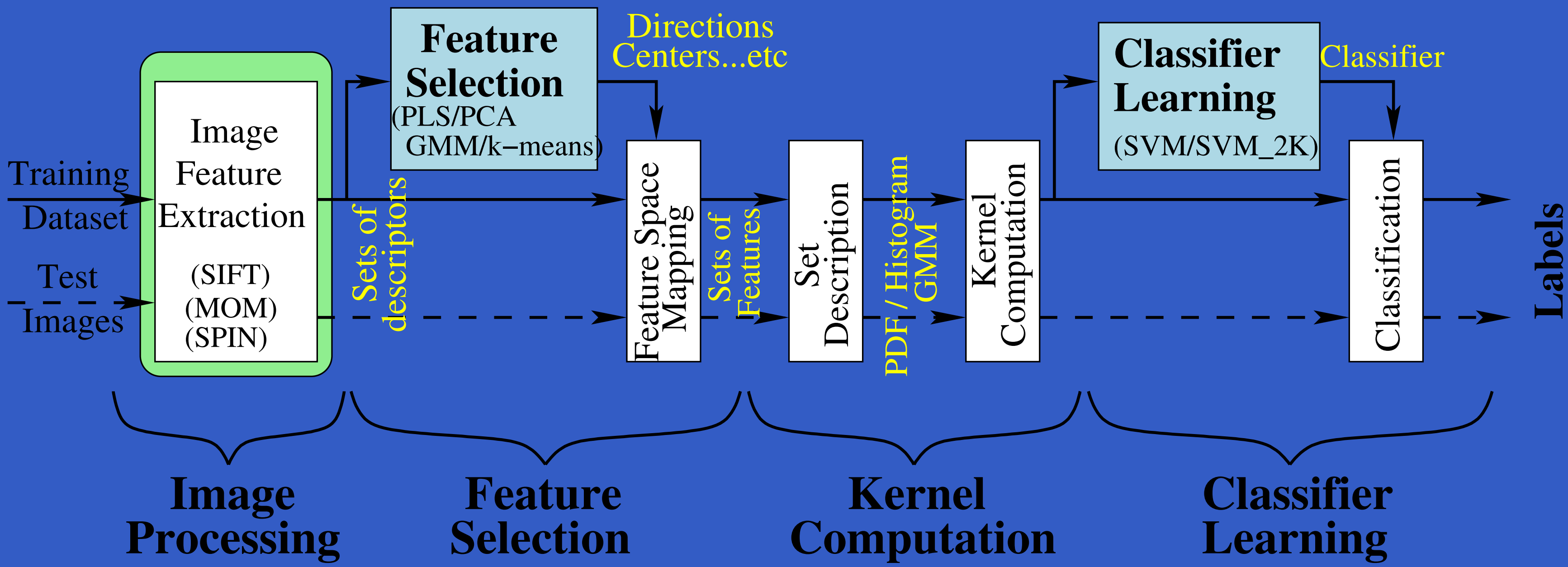
1. Image Processing – extract a set of interesting local patch descriptors from each image.

The "set-of-patches" approach to image categorisation.



1. Image Processing
2. Feature Selection – identify features of the patch descriptions most useful for categorisation.

The “set-of-patches” approach to image categorisation.



1. Image Processing
2. Feature Selection
3. Kernel Computation – compute a kernel between sets of features in each image.

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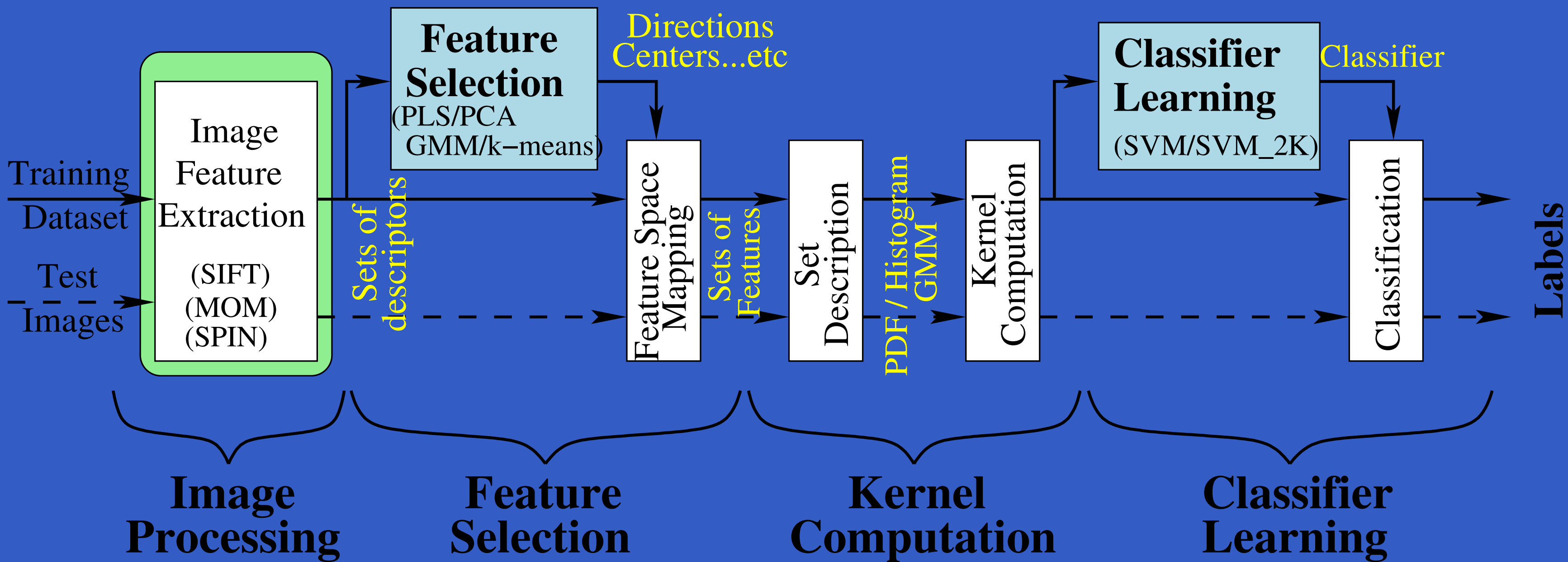

1. Image Processing
2. Feature Selection
3. Kernel Computation
4. Classifier Learning – learn a classifier from the computed kernels.

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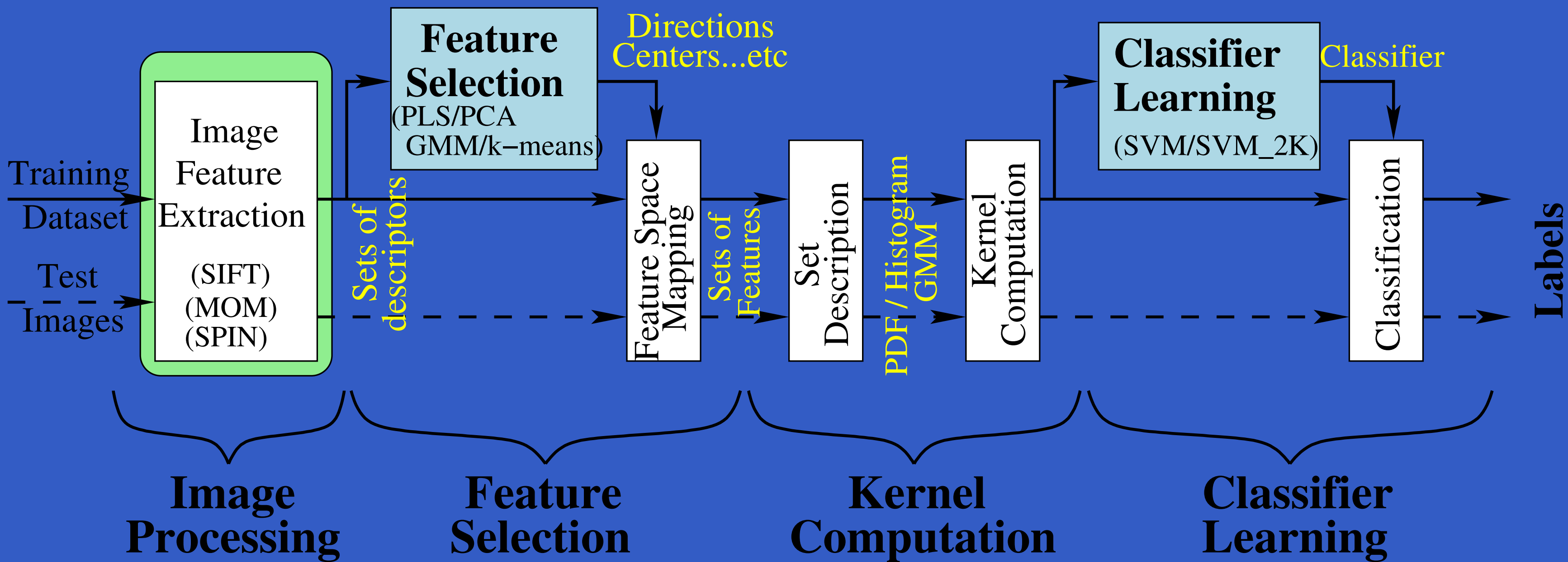

1. Image Processing

2. Feature Selection
3. Kernel Computation
4. Classifier Learning

Image Processing

Similar to many of the other approaches.

1. Patch detection – identify interesting patches in the image.
   - Lapacian of Gaussians – detects circular “blob like” structures [Lindeberg (1998)].
   - Scale invariant Harris-Affine – detects elliptical patches containing corners or highly textured parts of the image. [Mikolajczyk & Schmid (2004)]

Image Processing

Similar to many of the other approaches.

1. Patch detection – LoG or Harris-Affine.
2. Patch description – produce reproducible and robust descriptions of the patches.
   - SIFT – describes circular patch in terms of 8 smoothed directional image gradients at 16 positions within the patch. [D. Lowe 2004]

Image Processing

Similar to many of the other approaches.

1. Patch detection – LoG or Harris-Affine.
2. Patch description – SIFT
3. Output – a set of between 20 and 3000 128d SIFT patch descriptions per image

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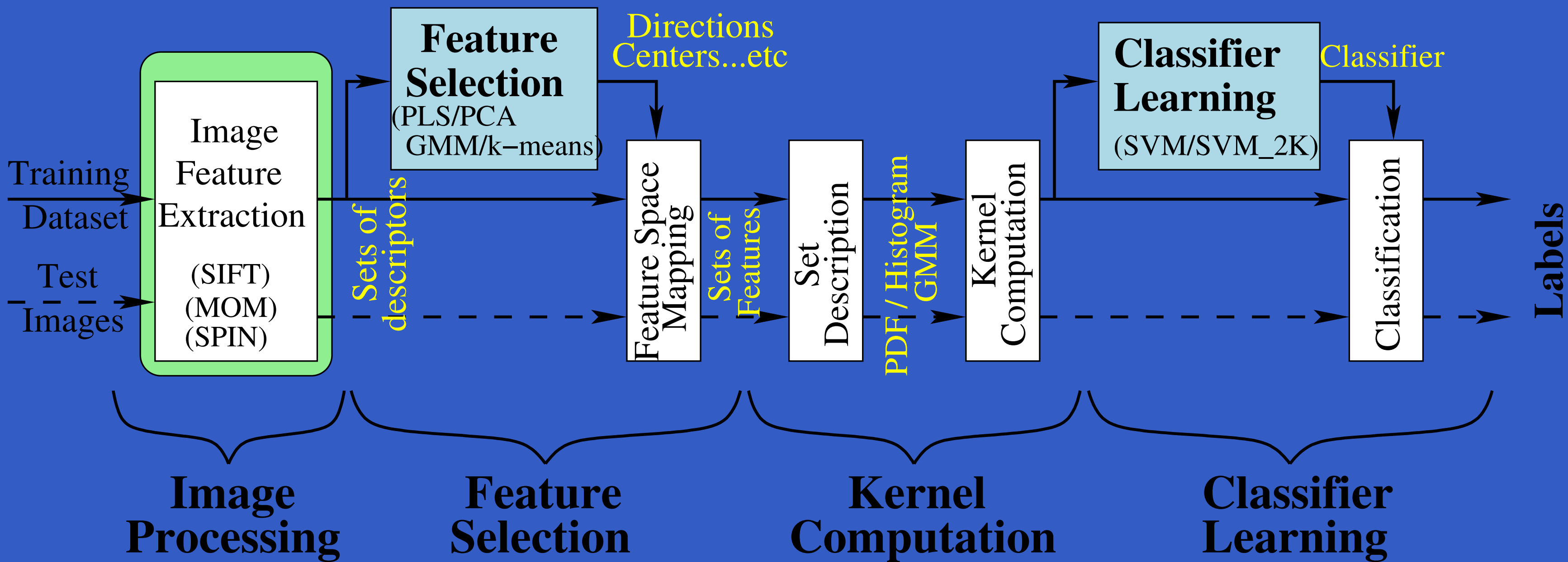
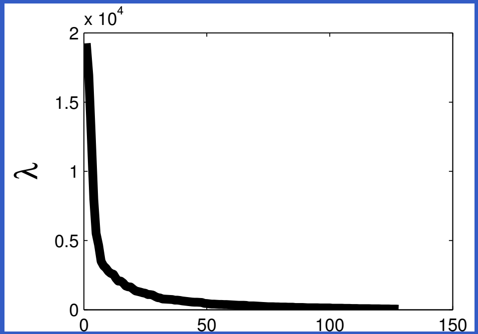


1. Image Processing
2. **Feature Selection**
3. Kernel Computation
4. Classifier Learning

Feature Selection

- SIFT descriptors high dimensional and contain a lot of redundant information.

  Eigenvalue decomposition of the data covariance shows that SIFTs dimensions are highly correlated



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Use feature selection techniques to identify most useful patch features for categorisation.

Feature Selection(2)

Many possible feature selection approaches, methods we have tried are,

1. **Clustering** – GMMs or k-Means used to identify points and regions in feature space which contain useful information.

   Then define new features, e.g. NN region membership or center distances.

2. **Sub-space mapping** – PCA or PLS used to identify feature space directions which contain useful information.

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Initial experiments indicated that PLS gave best results so only examine this here.

Feature Selection(4)— Partial Least Squares (PLS)

PLS is similar to PCA *except*

- takes account of output labels $Y \in \mathbb{R}^{N \times L}$,
- by finding *pairs* of directions $\mathbf{u}, \mathbf{v}$ which maximise projected data/output cross-covariance,

$$\mathbf{u}, \mathbf{v} = \underset{\mathbf{u},\mathbf{v}}{\operatorname{argmax}} [\operatorname{cov} \{X\mathbf{u}, Y\mathbf{v}\}]^2$$

- This is equivalent to finding the first eigenvector of,

$$\lambda \mathbf{u} = X^T Y Y^T X \mathbf{u}$$

- Can repeat this process after *deflating* X to remove information already used to get $> L$ directions,

$$X_{i+1} = X_i (I - \mathbf{u}_i \mathbf{u}_i^T)$$

(N.B. need to undo the deflations to get final feature directions)

Feature Selection(5)

- Given feature directions $\mathbf{u}_1, \mathbf{u}_2, \ldots \mathbf{u}_{d_2}$ compute new features $\hat{X}$ by projecting X onto these directions,

$$\hat{X} = X * [\mathbf{u}_1 \mathbf{u}_2 \ldots \mathbf{u}_{d_2}]$$

- Output is set of features per image

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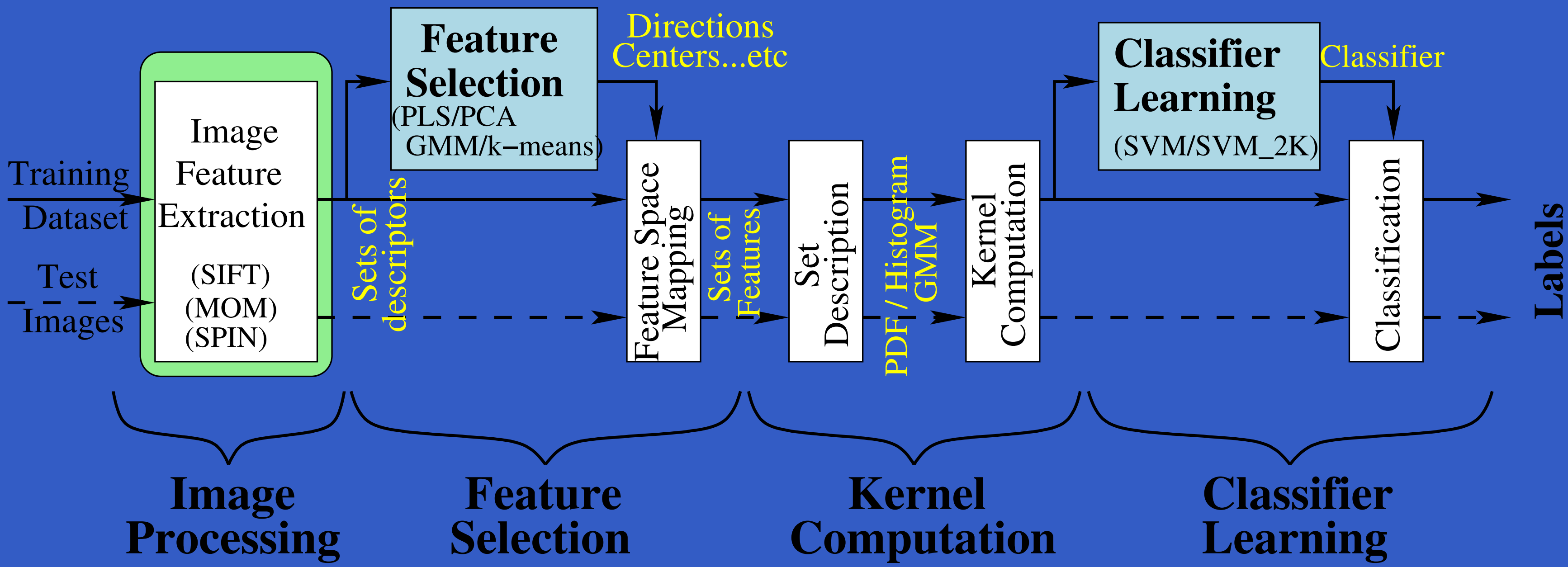

1. Image Processing
2. Feature Selection
3. **Kernel Computation**
4. Classifier Learning

Kernel Computation

- Input to this stage is set of feature vectors (one per detected patch) per-image
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- Input to this stage is set of feature vectors (one per detected patch) per-image
- Trying to categorise **images** not patches, so need a per-image kernel matrix for classifier learning
- Define a kernel function over sets of feature vectors to compute this kernel matrix. Compute this in 2 stages,
  1. Map from sets of features to a single description
  2. Compute a kernel between the descriptions

Kernel Computation(2) – Set $\rightarrow$ description mapping

- Represent image i's set of features, $\hat{X}_i$, as a parameterised density distribution,

$$\hat{X}_i \longrightarrow \rho(\mathbf{x}|\theta_i)$$

  Many possible density models, e.g. histograms, GMMs

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- For ease of kernel computation use a full-covariance Gaussian Probability Density Function (PDF),

$$\hat{X}_i \rightarrow \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_i, \Sigma_i)$$

  Use MAP to fit this model,
    - Provide regularisation for noise tolerance and capacity control,
    - Avoid singularities with low numbers of features.

Kernel Computation(3) – PDF Kernels

- Need a kernel between PDFs
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- Proving these produce valid kernels is difficult
- Use the Bhattacharyya affinity which is clearly a kernel,

$$K_{\mathsf{B}}(\mathbb{P}_1(\mathbf{x}), \mathbb{P}_2(\mathbf{x})) = \int_{-\infty}^{\infty} \sqrt{\mathbb{P}_1(\mathbf{x})}\sqrt{\mathbb{P}_2(\mathbf{x})}d\mathbf{x}$$

- K_{B} has an analytic solution for pairs of Gaussians

$$K_{\mathsf{B}}(\mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_1, \Sigma_1), \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_2, \Sigma_2)) =$$

$$\frac{1}{2}^{\frac{d}{2}} \Sigma_+^{-\frac{1}{2}} \Sigma_1^{-\frac{1}{4}} \Sigma_2^{-\frac{1}{4}} \exp\left[-\frac{1}{4}(\mu_1^T \Sigma_1^{-1} \mu_1 + \mu_2^T \Sigma_2^{-1} \mu_2) - \mu_+^T \Sigma_+^{-1} \mu_+\right]$$

where, $\Sigma_+ = (\Sigma_1^{-1} + \Sigma_2^{-1})^{-1}$ and $\mu_+ = \Sigma_1^{-1}\mu_1 + \Sigma_2^{-1}\mu_2$

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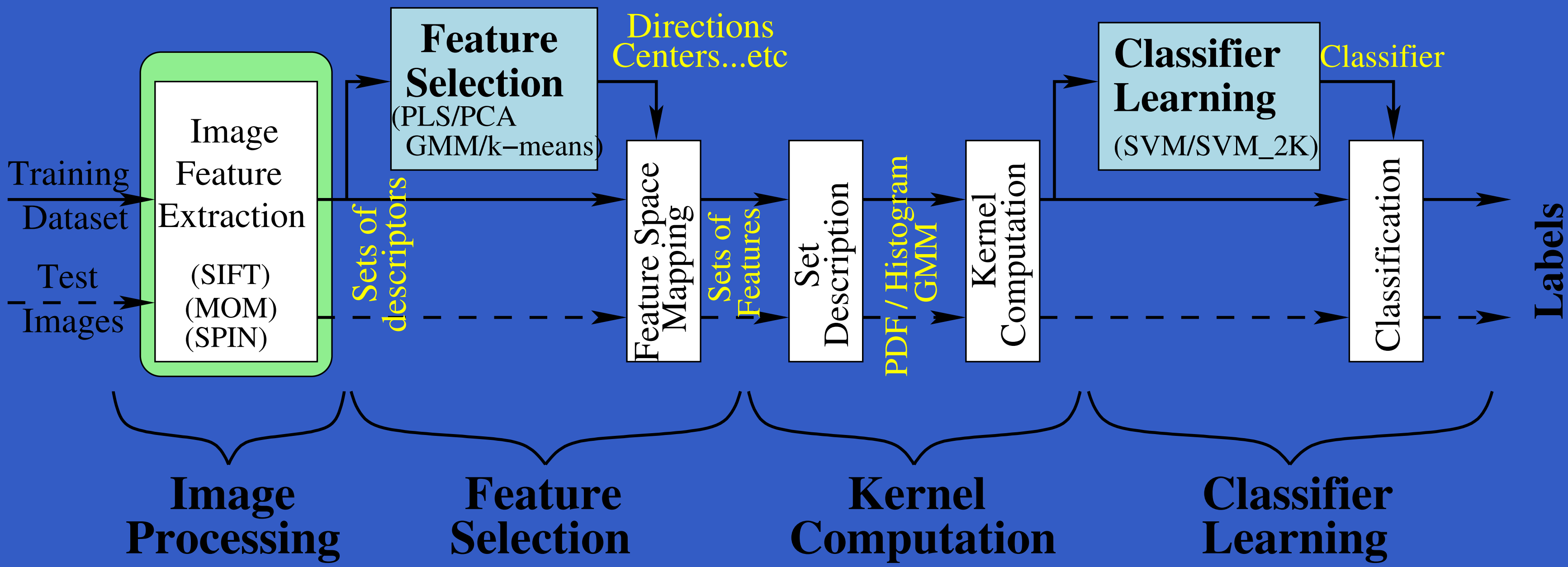

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Classifier Learning

We have conducted experiments using either a conventional SVM or our extension, SVM_2K.

- SVM_2K is a two-kernel extension of the SVM,
- Uses a synthesis constraint, ψ, to force each sub-SVMs output, h_A, h_B, to be correlated,

$$\psi(h_A(\mathbf{x}_i^A), h_B(\mathbf{x}_i^B)) \leq \delta$$

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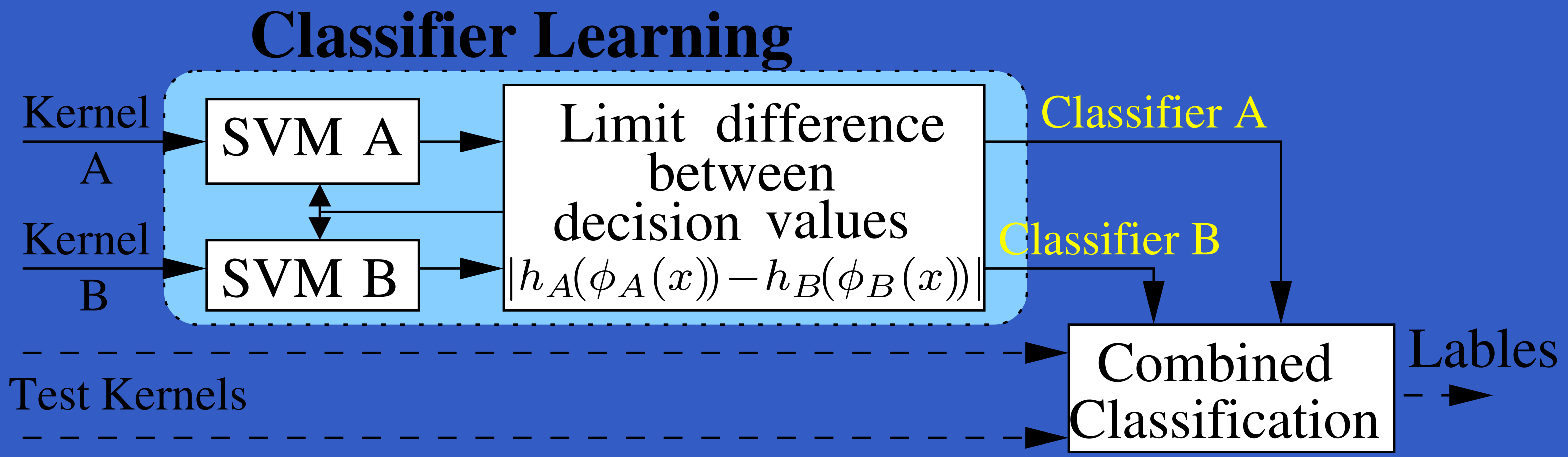
- Idea is that different views of the same object should have correlated signal but (hopefully) uncorrelated noise.
- This is sometimes called co-training or multi-view learning.

Classifier Learning(2) — SVM_2K



The modified primal optimisation problem is,

$$\min \frac{1}{2}(||w_A||_2^2 + ||w_B||_2^2) + \mathbf{1}^T(C_A\xi^A + C_B\xi^B + D\eta)$$

subject to

Synthesis $\dashrightarrow$ $\psi(\langle w_A, \phi_A(x_i^A)\rangle + b_A, \langle w_B, \phi_B(x_i^B)\rangle + b_B) \leq \eta_i + \epsilon,$

subSVM A $\dashrightarrow$ $y_i(\langle w_A, \phi_A(x_i^A)\rangle + b_A) \geq 1 - \xi_i^A,$

subSVM B $\dashrightarrow$ $y_i(\langle w_B, \phi_B(x_i^B)\rangle + b_B) \geq 1 - \xi_i^B,$

$$\xi^A \geq 0,\ \xi^B \geq 0,\ \eta \geq 0,\ i = 1, \ldots, m.$$

Classifier Learning(3) — SVM_2K

- Using $\psi(x) = \text{abs}(x)$ resulting problem has special structure which allows efficient solution, using;
  1. **Augmented Lagrangian**: To eliminate equality dual constraints
  2. **Conditional Gradient**: To solve problem with fixed Lagrangian multipliers
  3. **Linear Programming**: To derive the next approximation of the optimum.
- This approach has linear complexity which the key to the algorithms efficiency!
- It is **over 1000** times faster for this problem than general purpose optimisers.

Results – VOC `test1` EER

Pt. Detector	Learner	M'bikes	Bikes	People	Cars
LoG	SVM	94.9	86.8	83.3	91.3
Harris-Affine	SVM	94.0	85.1	84.1	89.8
LoG + Har-Aff	SVM_2K	**97.2**	**89.5**	**88.1**	**91.3**

`train` and `val` used for training and parameter tuning:

- Feature Selection: 20 dimensional PLS
- Same directions used for all categories
- MAP prior = training set covariance and mean, weighted to represent 10 “virtual” feature vectors
- SVM penalties: determined by cross-validation for each kernel.

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- PLS feature selection plus PDF kernels gives good basic performance
- LoG seems to be slightly better than Har-Aff, probably because generates more patches ($\approx$1000 vs. $\approx$100)
- Combining features with SVM_2K further improves performance

Conclusions & Further work

No surprises here,

- Feature selection is critical to performance ...
- as is identifying a good kernel function

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Future Work

- Alternative feature selection techniques
  - per-category feature selection
  - methods to suppress “non-object” patches
- Using more than 2 kernels in SVM_2K