

	Vasa 1 4 miles
	KEENELS VER 1 1 3854VI
	A STATE OF THE STA
	· Non hines Season Loundary
	Redict y=1 (=> 00+0, 4+0222+032122-71C
	Kedick y=1 (=) 00 +0 4, +0222
	=> ho a) - {1 (=> 0, + > 0)
100	
	else
	Our features one \$ x,1x2, x3, but now
	I have Colored to the
	well use ather 1 = ×1, (2 = ×2, 73 = ×1.
4	for example ?
New -	for example ?
5	
	on proximity to landmarks l', l', l'
	an proximity to landmorks l'il"
5 3 .	4= similarity (x, (1) = exp(-11x-111)
19.00	
	2.62
	1 = similarity (x, l2) = exp(-11x- e2)
	1 = similarity (x, l2) = exp(-11x- e2) 202)
	1 = similarity (x, l2) = exp(-11x- e2) 202)
	1 = similarity (x, l2) = exp(-11x- e2) 202)
	1 = similarity (x, l2) = exp(-11x- e2) 252) -gavesian Keinels
1	1 = similarity (x, (2) = exp(-11x- e2) 262) - gaverian Kersels - Kernels and gimilarity
100	1 = similarity (x, (2) = exp(-11x- e2) 262) - gaverian Kersels - Kernels and gimilarity
A.c.	1 = similarity (x, l2) = exp(-11x- e2) 252) . gavenan kessels . Kernels and similarity -if x ~ li => f ~ 1
A	1 = similarity (x, (2) = exp(-11x- e2) 262) - gaverian Kersels - Kernels and gimilarity
A	1 = similarity (x, l2) = exp(-11x- e2) 252) . gavenan kessels . Kernels and similarity -if x ~ li => f ~ 1
A	$f_{2} = similarity(X, \ell^{2}) = exp(-1 X - \ell^{2})$ $= 252$
A	$f_{2} = similarity(X, \ell^{2}) = exp(-1 X - \ell^{2})$ $= 252$
A	1 = similarity (x, l2) = exp(-11x- e2) 252) . gavenan kessels . Kernels and similarity -if x ~ li => f ~ 1
A	$f_{2} = similarity(X, \ell^{2}) = exp(-1 X - \ell^{2})$ $= 252$
A	$f_{2} = similarity(X, \ell^{2}) = exp(-1 X - \ell^{2})$ $= 252$

· SVM with Keriels
$\frac{\Im \left(\left(\frac{2}{5}\right)^{i} \cos t_{1}\left(0^{T} \right)^{i}\right) + \left(1 - y^{i}\right) \cos t_{0}\left(0^{T} \right)^{i} + \frac{1}{2} \underbrace{5}_{j=1}^{\infty}$
C= 1 SC)) =) lover hise chieb warance
C= 1 S C >>> => lower bias i high warance
62: So2>> => f. will very more somothly => higher bias, low wasance
0?(< => f: will vary less smoothly 1 fi
- Using SPV packages - Chaia of C
- Chaia of C - Chaia of kunel
6x: lines konel => y=1 (=> 0+x>0
- Frature scaling before using Gaussian Levrell1
• CPV(11 P)
ospv multicless classification
-> 1 vs all method
THE STATE OF THE S

2 · If nr m => SVM with gaussian kernel 3 · If ne m => Create /add more features: & 2 · If ne m => Create /add more features: & 2 · If ne m => Create /add more features: & 2 · If ne m => Create /add more features: & 2 · If ne m => Create /add more features: & 2 · If ne m => Create /add more features: & 2 · If ne m => Create /add more features: & 2 · If ne m => Create /add more features: & 3 · If ne m => Create /add more features: & 4 · If ne m => Create /add more features: & 5 · If ne m => Create /add more features: & 5 · If ne m => Create /add more features: & 5 · If ne m => Create /add more features: & 5 · If ne m => Create /add more features: & 6 · If ne m => Create /add more features: & 6 · If ne m => Create /add more features: & 6 · If ne m => Create /add more features: & 6 · If ne m => Create /add more features: & 7 · If ne m => Create /add more features: & 8 · If ne m => Create /add more features: & 8 · If ne m => Create /add more features: & 8 · If ne m => Create /add more features: & 9 · If ne m => Create /ad		
1. If no m => LR or SVM without knowle (linear) 2. If no m => SVM with gaussian kernel 3. If no m => Create /add more features: R 20 1 Language poblems this is not typical at all training set always way byser Than wriber of features. 4 Never in the works (chely to perform nice in every & exemptance, but may be slower to train		· Carrobs and save VS SICM
1. If norm => LR or SVM without permil (linear) 2. If norm => SVM with gaussian Kernel 3. If norm => Greate /add more features: R 20. 1 21. In x m => Greate /add more features: R 20. 1 21. In x m => Greate /add more features: R 20. 1 21. In x m => Greate /add more features: R 22. It norm => Greate /add more features: R 23. It norm => Greate /add more features: R 24. It norm => Greate /add more features: R 25. It norm => Greate /add more features: R 26. It norm => Greate /add more features: R 26. It norm => Greate /add more features: R 27. It norm => Greate /add more features: R 28. It norm => Greate /add more features: R 29. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 21. It norm => Greate /add more features: R 22. It norm => Greate /add more features: R 23. It norm => Greate /add more features: R 24. It norm => Greate /add more features: R 25. It norm => Greate /add more features: R 26. It norm => Greate /add more features: R 27. It norm => Greate /add more features: R 28. It norm => Greate /add more features: R 29. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 21. It norm => Greate /add more features: R 22. It norm => Greate /add more features: R 23. It norm => Greate /add more features: R 24. It norm => Greate /add more features: R 25. It norm => Greate /add more features: R 26. It norm => Greate /add more features: R 27. It norm => Greate /add more features: R 28. I		Cost the refression > > V
1. If norm => LR or SVM without permil (linear) 2. If norm => SVM with gaussian Kernel 3. If norm => Greate /add more features: R 20. 1 21. In x m => Greate /add more features: R 20. 1 21. In x m => Greate /add more features: R 20. 1 21. In x m => Greate /add more features: R 22. It norm => Greate /add more features: R 23. It norm => Greate /add more features: R 24. It norm => Greate /add more features: R 25. It norm => Greate /add more features: R 26. It norm => Greate /add more features: R 26. It norm => Greate /add more features: R 27. It norm => Greate /add more features: R 28. It norm => Greate /add more features: R 29. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 21. It norm => Greate /add more features: R 22. It norm => Greate /add more features: R 23. It norm => Greate /add more features: R 24. It norm => Greate /add more features: R 25. It norm => Greate /add more features: R 26. It norm => Greate /add more features: R 27. It norm => Greate /add more features: R 28. It norm => Greate /add more features: R 29. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 21. It norm => Greate /add more features: R 22. It norm => Greate /add more features: R 23. It norm => Greate /add more features: R 24. It norm => Greate /add more features: R 25. It norm => Greate /add more features: R 26. It norm => Greate /add more features: R 27. It norm => Greate /add more features: R 28. I	1	
1. If norm => LR or SVM without permil (linear) 2. If norm => SVM with gaussian Kernel 3. If norm => Greate /add more features: R 20. 1 21. In x m => Greate /add more features: R 20. 1 21. In x m => Greate /add more features: R 20. 1 21. In x m => Greate /add more features: R 22. It norm => Greate /add more features: R 23. It norm => Greate /add more features: R 24. It norm => Greate /add more features: R 25. It norm => Greate /add more features: R 26. It norm => Greate /add more features: R 26. It norm => Greate /add more features: R 27. It norm => Greate /add more features: R 28. It norm => Greate /add more features: R 29. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 21. It norm => Greate /add more features: R 22. It norm => Greate /add more features: R 23. It norm => Greate /add more features: R 24. It norm => Greate /add more features: R 25. It norm => Greate /add more features: R 26. It norm => Greate /add more features: R 27. It norm => Greate /add more features: R 28. It norm => Greate /add more features: R 29. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 20. It norm => Greate /add more features: R 21. It norm => Greate /add more features: R 22. It norm => Greate /add more features: R 23. It norm => Greate /add more features: R 24. It norm => Greate /add more features: R 25. It norm => Greate /add more features: R 26. It norm => Greate /add more features: R 27. It norm => Greate /add more features: R 28. I		1 = 0 of featires ; un = 0 of training examples
2 · If nrm => SVM with gaussian Kernel 3 · If nrm => Greate /add more features: R 60 1 In python problems this is not typical at all Faving set always way byser than number of features. P 4 Neval retworks likely to perform nice in every & coverstance, but may be slower to train		
3. If nem => Create /add more features: R 20 1 20 1 20 1 21 pythose problems there is not typical at all training set always way 5: ger Than surper of features. P 4 Neval networks likely to perform nice in every & arunstance, but may be slower to train	1	· If ny m => LR or SVM without keynl (linear)
3. If nem => Create /add more features: R 20 1 20 1 20 1 21 pythose problems there is not typical at all training set always way 5: ger Than surper of features. P 4 Neval networks likely to perform nice in every & arunstance, but may be slower to train		Discourse Continued and many to the part of the continued to
3. If nem => Create /add more features: R 20 1 20 1 20 1 21 pythose problems there is not typical at all training set always way 5: ger Than surper of features. P 4 Neval networks likely to perform nice in every & arunstance, but may be slower to train	2	·If nom=> SVM with agression Kernel
3. If nem => Create (add more features? & 20 1. In python problems this is not typical at all training set always way bigger than number of features. 4 Never networks likely to perform nice in every & armstance, but may be slower to train		
In python problems this is not typical at all training set always way bigger than number of features. P # Neural networks likely to perform nice in every & arunstance, but may be plower to train	7	178 6 1 (1)
In python problems this is not typical at all training set always way bigger than number of features. P # Neural networks likely to perform nice in every & arunstance, but may be plower to train	: 1	The Man Create ade more features
than surber of festeres. 4 Never networks likely to perform nice in every & corunstance, but may be slower to train		30 1
# Neval networks lobely to perform nice in every & corunstance, but may be slower to train		
# Never networks likely to perform nice in every & arunstance, but may be slower to train	4-A1	In pythan poblems this is not typical
# Never networks likely to perform nice in every & arunstance, but may be slower to train	11	at all training set always way bycer
# Never networks likely to perform nice in every & arunstance, but may be slower to train		than surper of features.
# Never networks likely to perform nice in every & arunstance, but may be slower to train	vil	P (Carotti.
Service sound of the service of the	3	
Service sound of the service of the		4 Neval networks likely to perform nice
Service sound of the service of the		in every & wrunstance, but may be slower
Service sound of the service of the	11	to train
Mind of the state		
Million and the solution was soldier was		Marial of the control
Million program for a super particular restriction Vgs.		
· PPV "whicher charifica hea	111	
with a state of the state of th		A CONTRACT STATE AND ASSESSED STATE OF THE S
		with experience restaution volume
	,	
	Maria .	