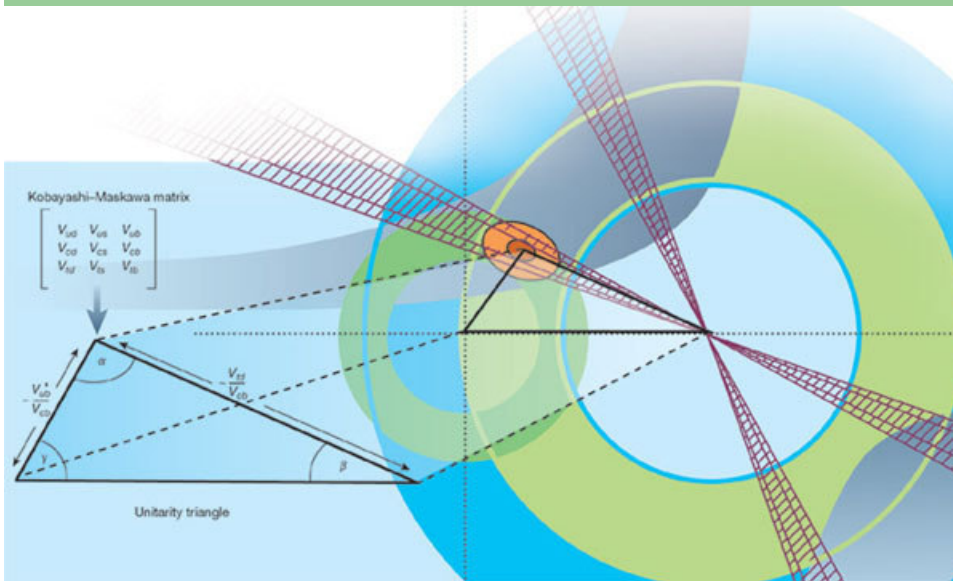


Flavor tagging – status & prospects

M. Bruinsma, UCI
Tools Workshop
Oct 1st 2005, SLAC



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History

Name	Type	Nr of cat.'s	Q
Elba	cut-based + Neural Net	4	25.0(8)%
Moriond	Neural Net	4	29.3(6)%
Tag04	Neural Net	6	30.5(4)%
Belle	Lookup table	6	28.8(6)%

	Run 1-4 (PRL)		
	Eff.	ω	Q
Lepton	0.086(1)	0.032(8)	0.075(2)
Kaon I	0.109(1)	0.046(7)	0.090(2)
Kaon II	0.171(2)	0.156(6)	0.081(2)
KaonPion	0.137(1)	0.237(7)	0.038(2)
Pions	0.145(1)	0.330(7)	0.017(1)
Other	0.100(1)	0.441(8)	0.003(1)
Total			0.305(4)

October 1st 2005

M. Bruinsma

Documentation

BADs:

BAD 242 : User guide on tagging tools

BAD 317 : Moriond tagger

BAD 729 : detailed description of Tag04

BAD 1025 : NIM paper draft – in preparation

Webpage with recipes, documentation, links to talks, etc.:

<http://www.slac.stanford.edu/BFROOT/www/Physics/Tools/Tagging/Main/index.html>

Current activities

Re-write of NN training/testing package BtgTest (done)

- based on PERL + ROOT macros
- retraining and testing made easier for us

Efforts to (further) improve tagging performance:

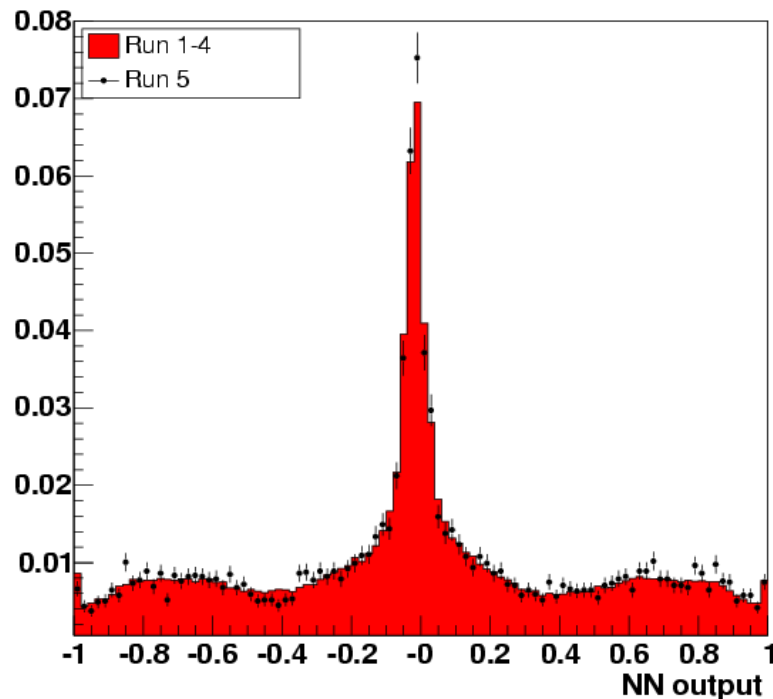
- adding new inputs, composites – not fruitful so far
- changing network architecture – not fruitful so far
- different types of classifiers (→ see Ilya's talk)
- **improved training methods**
- note: do not expect much higher Q's in the future anymore...

Validation:

- R18 validation
- Run 5 validation
- Note: tagging parameters ($\omega, \Delta\omega, \text{eff}, Q$) are specific to data set and release
 - e.g. expect more muon tags with LST
 - we expect benefits from higher track reconstruction eff in R18
 - we will provide tagging parameters on standardized data sets

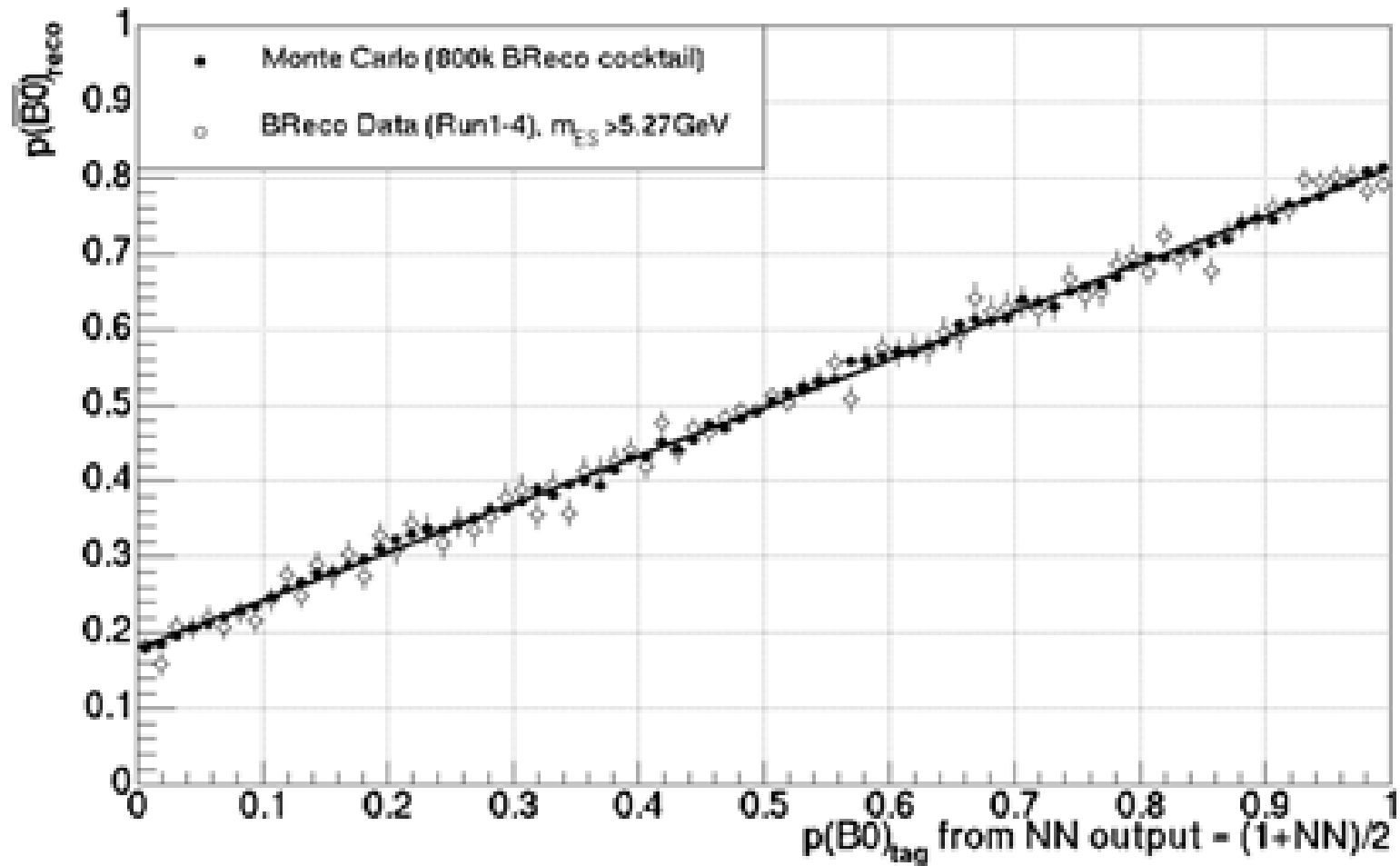
Run 5 tagging performance

NN output

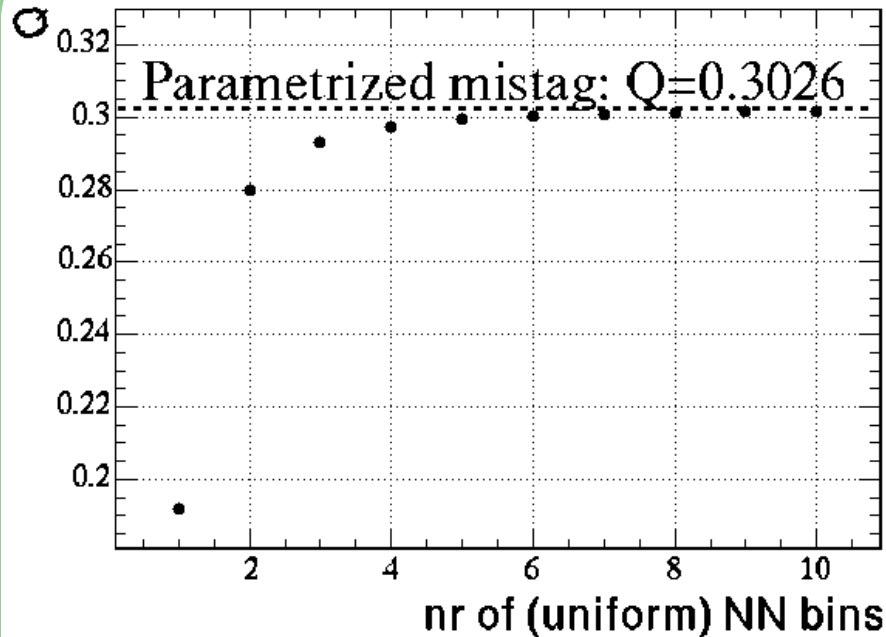


	Run 1-4 (PRL)			Run 5 so far		
	Eff.	ω	Q	Eff.	ω	Q
Lepton	0.086(1)	0.032(8)	0.075(2)	0.069(27)	0.056(42)	0.054(24)
Kaon I	0.109(1)	0.046(7)	0.090(2)	0.113(23)	0.061(36)	0.087(23)
Kaon II	0.171(2)	0.156(6)	0.081(2)	0.170(20)	0.112(32)	0.102(21)
KaonPion	0.137(1)	0.237(7)	0.038(2)	0.128(25)	0.267(32)	0.028(11)
Pions	0.145(1)	0.330(7)	0.017(1)	0.147(24)	0.304(39)	0.023(10)
Other	0.100(1)	0.441(8)	0.003(1)	0.102(30)	0.467(48)	0.000(1)
Total			0.305(4)			0.29(4)

Parametrizing mistag rates



$\omega(\text{NN})$ – statistical precision



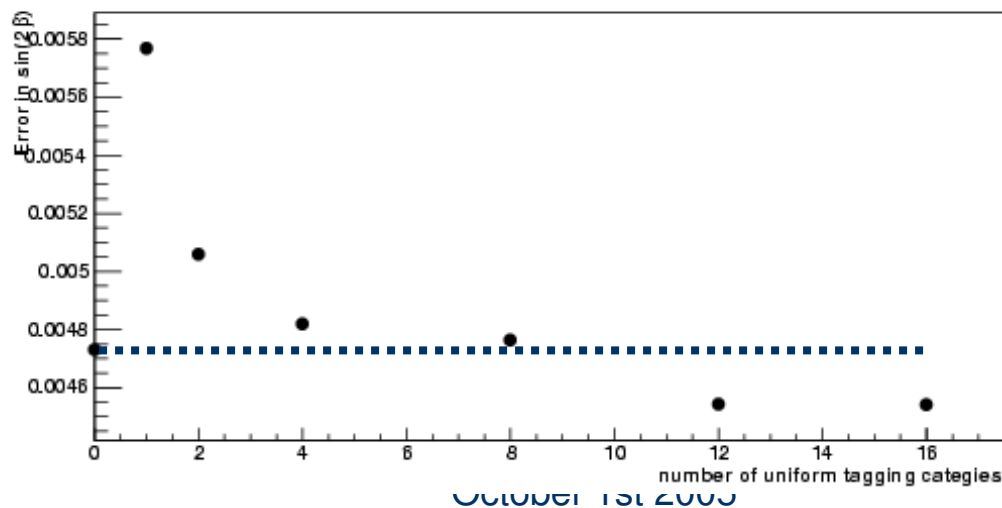
$$Q = \sum_{i=1}^{ncats} \varepsilon_i D_i^2 = \sum_{i=1}^{ncats} \varepsilon_i \overline{NN}_i^2$$

$$\sigma(\sin(2\beta)) \propto \sqrt{Q}$$

~ 10% improvement in Q

~ 3% improvement in $\sigma(\sin(2\beta))$

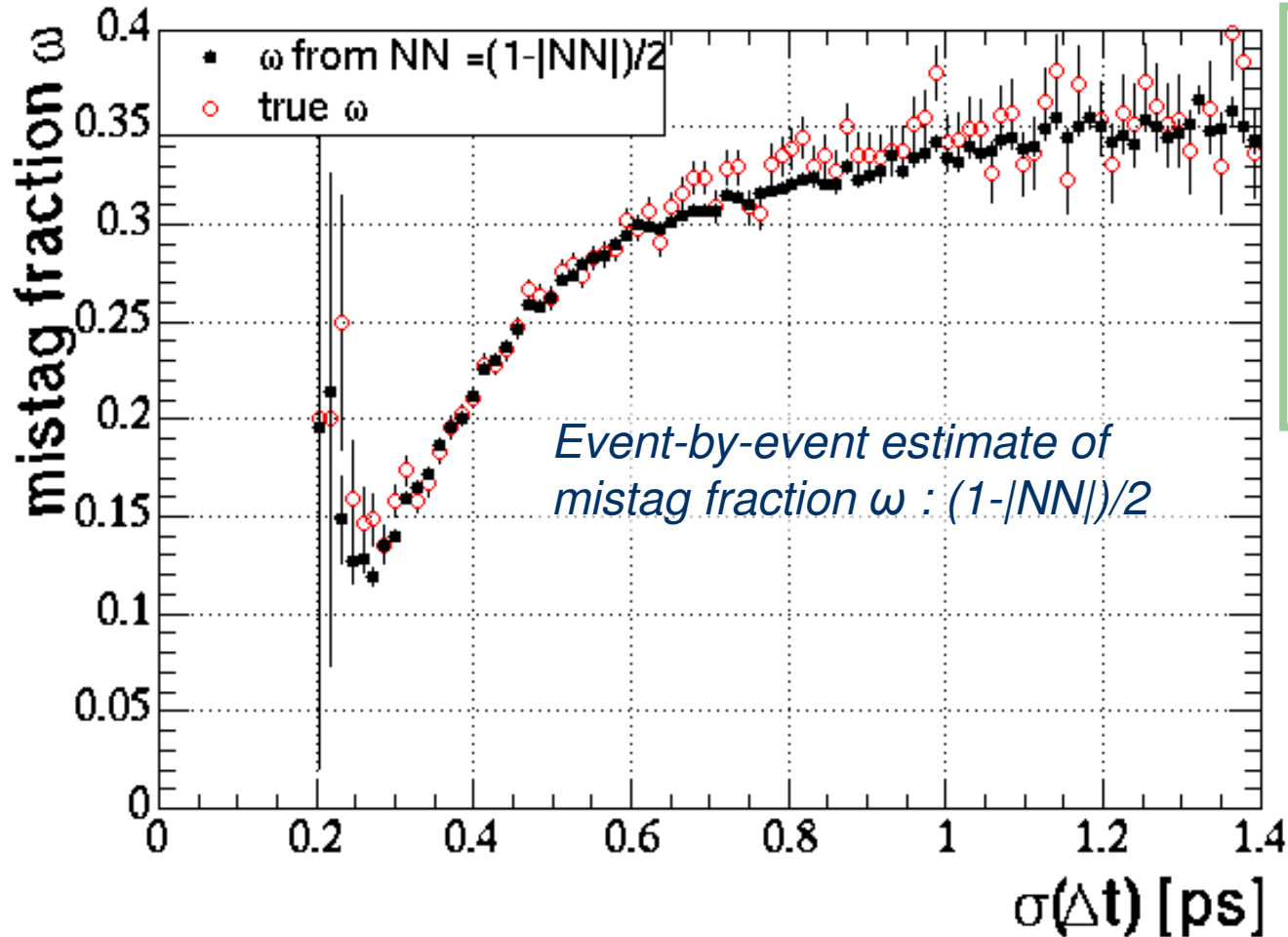
Statistical error in $\sin(2\beta)$



M. Bruinsma

$\omega - \sigma(\Delta t)$ correlation

Tag04 - MC - all tagging categories



Correlation between mistag fraction ω and the resolution in Δt is due the fact that low momentum particles give both imprecise vertices and uncertain tags.

correlation effectively neutralized with 6 categories (4 was too little)

Fitted parametrization

	MC - Parametrized raw
$\sin(2\beta)$	0.7099 ± 0.0048
$\omega_{\text{offset}}^{\text{signal}}$ Lepton	-0.0016 ± 0.0012
$\omega_{\text{offset}}^{\text{signal}}$ Kaon1	-0.0031 ± 0.0014
$\omega_{\text{offset}}^{\text{signal}}$ Kaon2	0.0030 ± 0.0015
$\omega_{\text{offset}}^{\text{signal}}$ KaonPion	0.0032 ± 0.0020
$\omega_{\text{offset}}^{\text{signal}}$ Pions	-0.0005 ± 0.0021
$\omega_{\text{offset}}^{\text{signal}}$ Other	-0.0080 ± 0.0026
$\omega_{\text{slope}}^{\text{signal}}$ Lepton	1.0065 ± 0.0436
$\omega_{\text{slope}}^{\text{signal}}$ Kaon1	1.0164 ± 0.0233
$\omega_{\text{slope}}^{\text{signal}}$ Kaon2	1.0229 ± 0.0104
$\omega_{\text{slope}}^{\text{signal}}$ KaonPion	1.0046 ± 0.0079
$\omega_{\text{slope}}^{\text{signal}}$ Pions	0.9856 ± 0.0058
$\omega_{\text{slope}}^{\text{signal}}$ Other	0.9906 ± 0.0061
$\Delta\omega^{\text{signal}}$ Lepton	0.0011 ± 0.0020
$\Delta\omega^{\text{signal}}$ Kaon1	-0.0015 ± 0.0021
$\Delta\omega^{\text{signal}}$ Kaon2	-0.0087 ± 0.0021
$\Delta\omega^{\text{signal}}$ KaonPion	-0.0267 ± 0.0025
$\Delta\omega^{\text{signal}}$ Pions	0.0607 ± 0.0026
$\Delta\omega^{\text{signal}}$ Other	0.0511 ± 0.0032

Slopes and intercepts from full simultaneous fit on MC (800k BReco + 600k B0gold):

Offset ~ 0
Slope ~ 1

$$\omega = \omega_{\text{offset}} + \omega_{\text{slope}} \left(\frac{1 - |NN|}{2} \right) \pm \Delta\omega$$

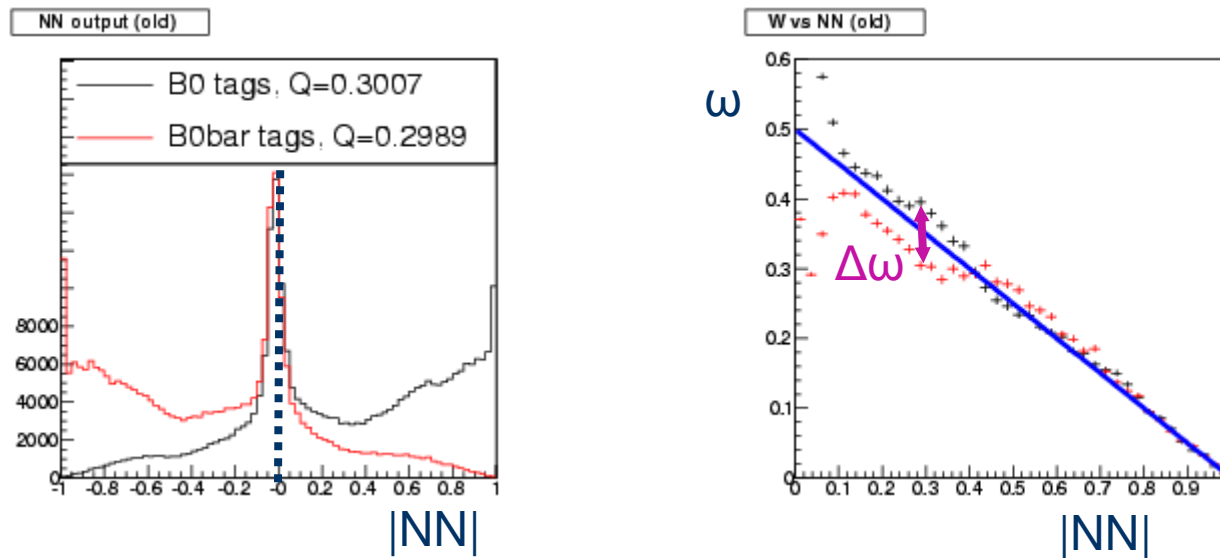
*No splitting
(GG resolution model)*

	Parametrized - Tag/Notag
$\sin(2\beta)$	0.7038 ± 0.0042
$\Delta\omega^{\text{signal}}$ Tagged	0.0090 ± 0.0008
$\omega_{\text{offset}}^{\text{signal}}$ Tagged	-0.0003 ± 0.0009
$\omega_{\text{slope}}^{\text{signal}}$ Tagged	0.9956 ± 0.0044

Improvements in training

Problem: NN output is asymmetric between B^0 and \bar{B}^0 :

- accommodated in CP fits with floating $\Delta\omega$
- prevented use of NN output as *per-event probability* in Summer04

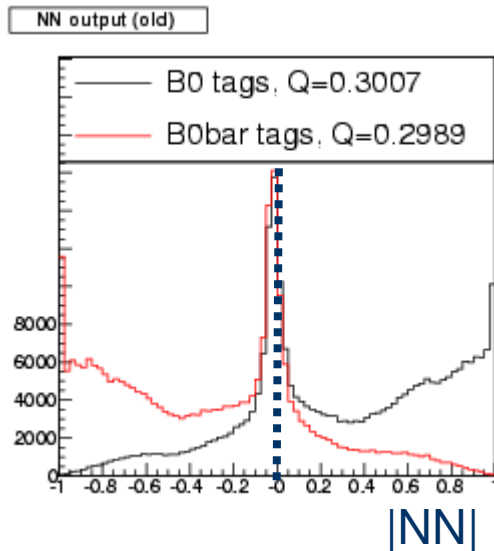


	Cut	ω	$\Delta\omega$
Lepton	$ \text{NN} > 0.8$	0.032(8)	-0.004(8)
Kaon I	$ \text{NN} > 0.8$	0.046(7)	-0.013(9)
Kaon II	$0.6 < \text{NN} < 0.8$	0.156(6)	-0.013(8)
KaonPion	$0.4 < \text{NN} < 0.6$	0.237(7)	-0.003(9)
Pions	$0.2 < \text{NN} < 0.4$	0.330(7)	0.049(9)
Other	$0.1 < \text{NN} < 0.2$	0.441(8)	0.022(11)

NN output as probability

The NN output is a (tag flavor) probability if (see Bishop):

- input data can be approximated with sum of Gaussians
- sufficient number of hidden nodes



In the past: number of B0 tags and B0bar tags not the same in the training sample:

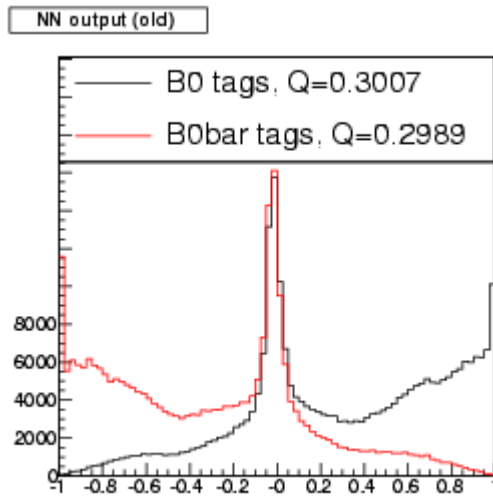
- posterior probability (NN output) for events with hardly any tagging information = prior probability = $N(B0)/(N_{tot})$ in training
- leads to nonzero $\Delta\omega$ for events with small $|NN|$

New strategy:

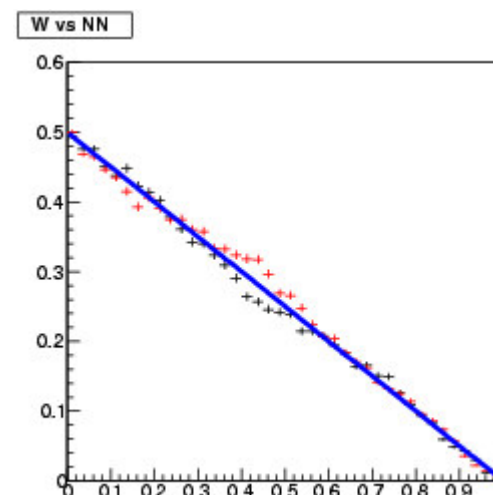
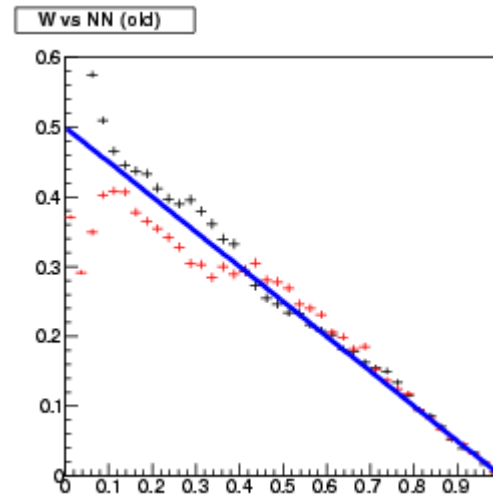
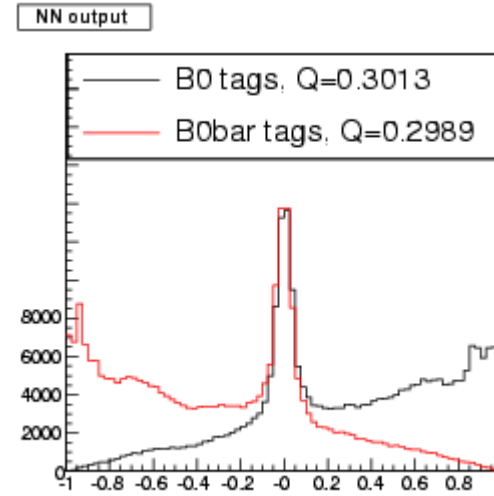
- retrain all sub-taggers with flavor as training target value
- enforce equal nr of events in training
- duplicate training patterns with flavor-mirrored copy

Results of new training

Before



After



Summary & Plans

- NIM paper in the making
- Run 5, R18 validation
 - Help welcome from 1 grad student (service work!)
- Will provide tagging parameters on standard data sets
- Still exploring ways to improve Q
 - Ilya is investigating extra inputs and alternative classifiers
 - Many studies done in the past, Tag04 close to optimal
 - Try all-in-one training (one NN with all sub-taggers)
- Will provide improved version of Tag04 (Tag06?) with more symmetrical NN output
 - Useful for parametrized mistag rates in time-dependent analysis
 - Hopefully will be able to increase Q as well