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features: (48842, 108)
accuracy: 0.849330518015
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A nice aspect of an RF model is that it provides a direct way to assess the importance of features (in terms of their predictive power).

In [19]:
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clf = RandomForestClassifier()
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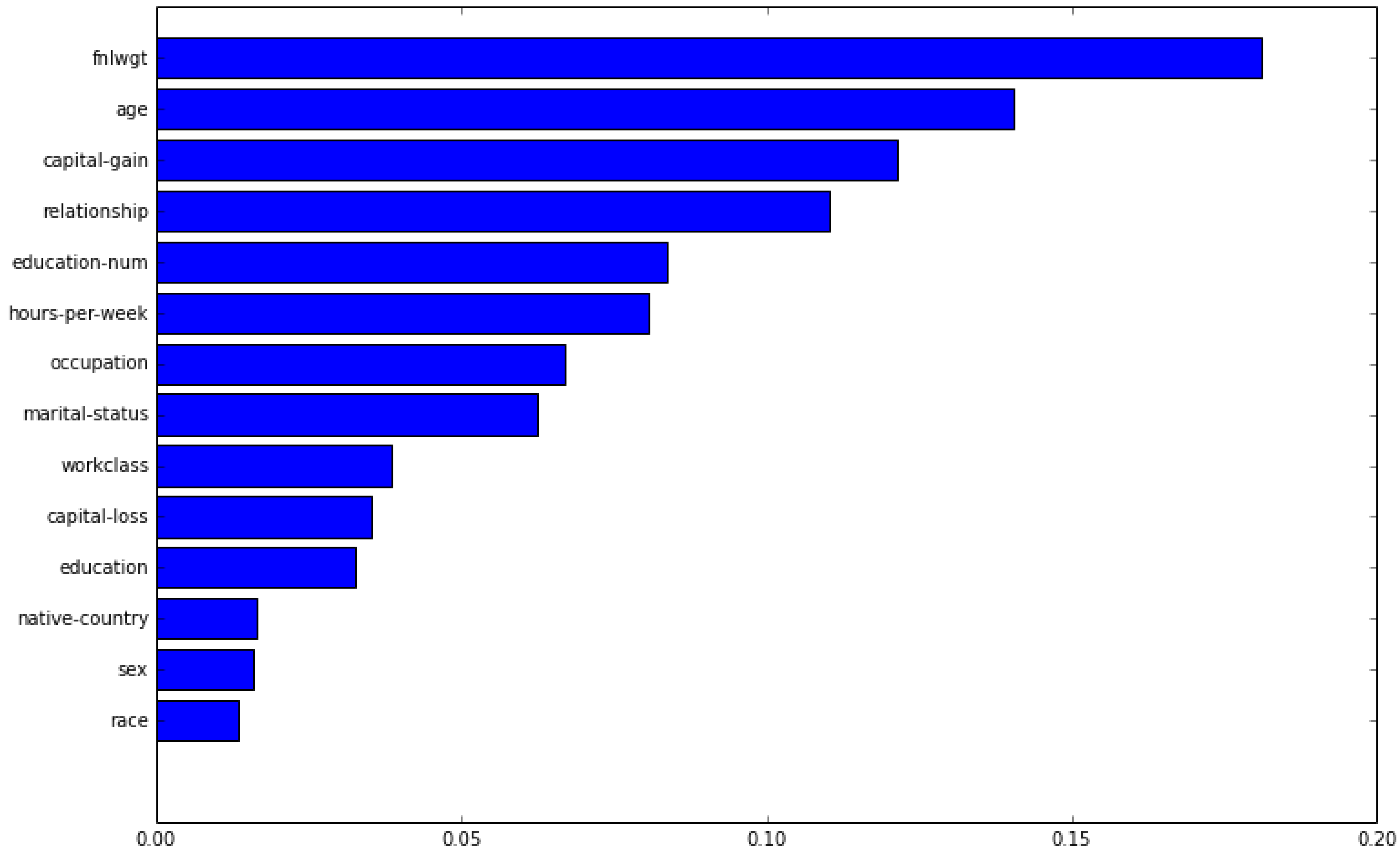

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In [31]:

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clf = RandomForestClassifier(max_features=None) # the default is sqrt(n_features), here we want to use them all
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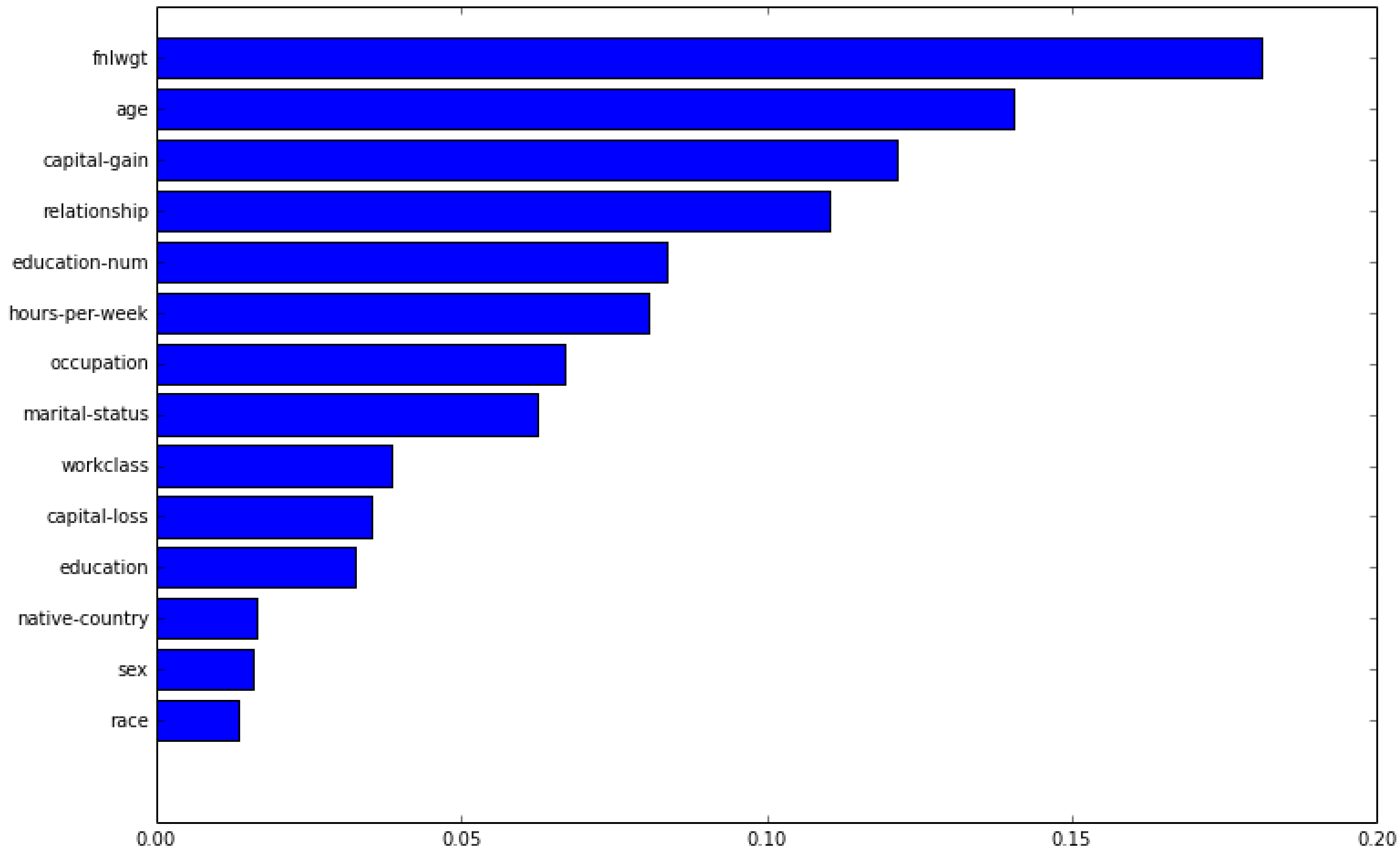

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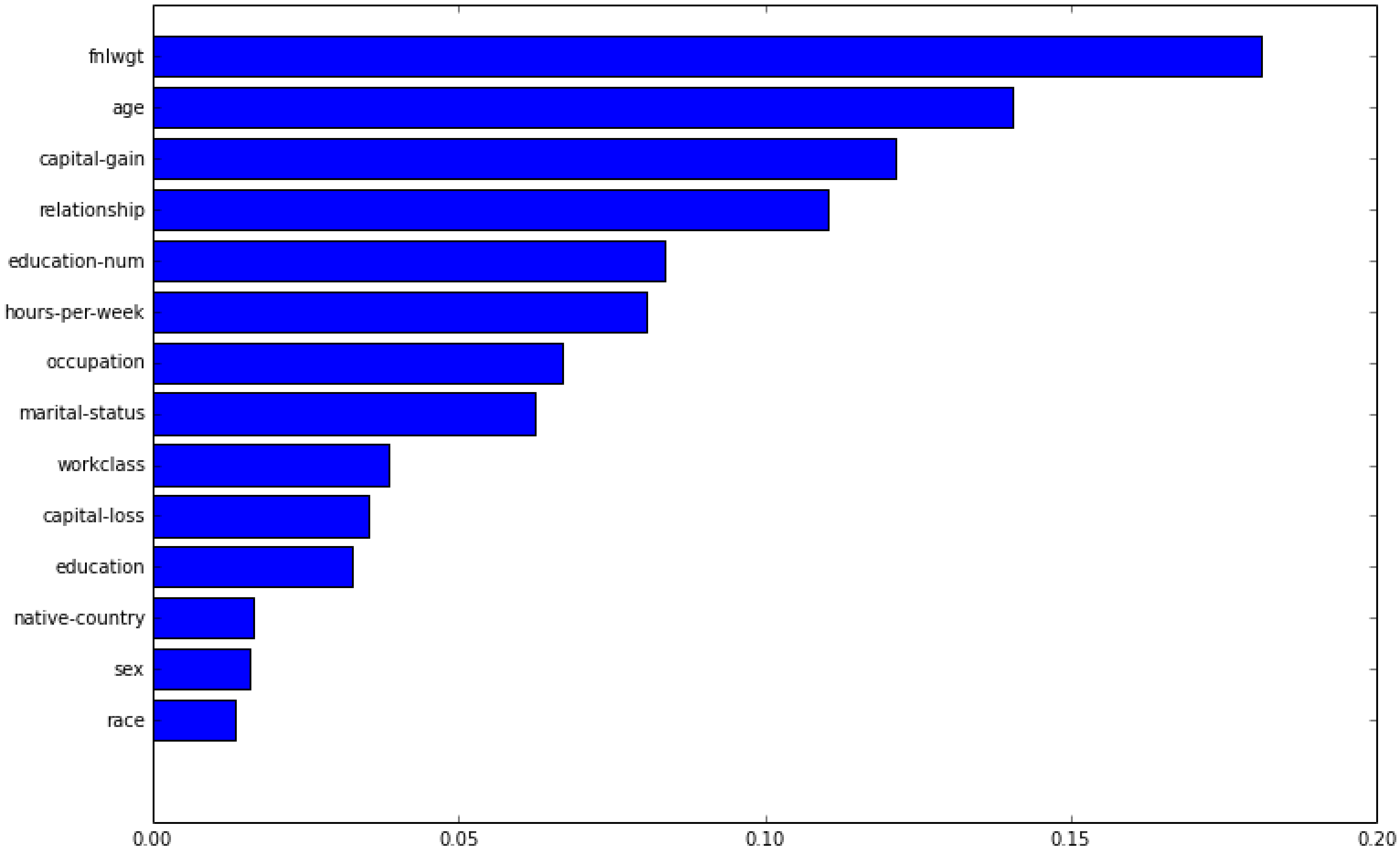

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