sparseS0s

February 5, 2019

Fitting sparse s_0s sets to lower include lower s_0s into the fit. Fits always contain ten s_0s. We fitted the kinematic, cubic and quartic weights for diferent sparse setups (take every second, every third, ... s_0). We probe for $s_{min} < 1GeV^2$.

```
In [2]: exec(open('initNotebook.py').read())
```

1 Load Data

```
In [4]: weights = ['wCube', 'wKin', 'wQuart']
        s0sMin = ['0.25', '0.475', '0.7', '0.925', '1.15', '1.375', '1.6', '1.95']

        indexList = []
        for weight in weights:
            for sMin in s0sMin:
                indexList.append(weight+sMin)


        df = pd.read_csv('../../FESR/configurations/2019/sparseS0/fits.csv', header=1)
        df.index = indexList
        # exclude not converged fits
        df = df[df['status']==0]
        wKin = df[7:14]
        wCube = df[0:7]
        wQuart = df[14:21]
        print(df.loc[: , ['chiDof', 'alpha', 'c6', 'c8']])
```

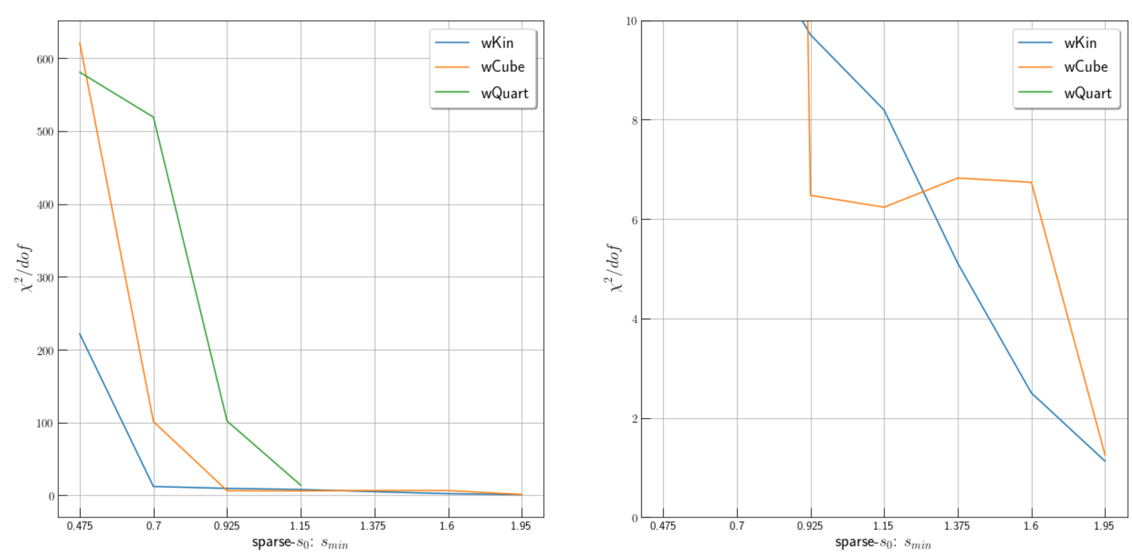
```
                chiDof     alpha        c6        c8
wCube0.475  621.113598  0.251979  0.017404  0.002315
wCube0.7    101.318873  0.296483 -0.100862 -0.027107
wCube0.925    6.475990  0.317996 -0.168569 -0.032908
wCube1.15     6.237693  0.317627 -0.165367 -0.031522
wCube1.375    6.824519  0.316832 -0.156248 -0.026802
wCube1.6      6.738773  0.319508 -0.190680 -0.047847
wCube1.95     1.250837  0.326473 -0.317688 -0.143137
wKin0.475   221.543734  0.288498 -0.127403 -0.047502
wKin0.7      12.250365  0.321578 -0.204496  0.047725
wKin0.925     9.707789  0.315771 -0.166135  0.049673
```

```
wKin1.15        8.193081  0.316996 -0.192990  0.020896
wKin1.375       5.109344  0.322636 -0.346324 -0.164277
wKin1.6         2.499764  0.328066 -0.538454 -0.431821
wKin1.95        1.127803  0.323164 -0.305910 -0.007625
wQuart0.475   580.765056  0.233311  0.033408  0.004707
wQuart0.7     519.107169  0.254503  0.014151  0.001032
wQuart0.925   102.070431  0.294491 -0.060142 -0.014340
wQuart1.15     14.057825  0.310799 -0.106915 -0.023816
```

```
In [10]: fig, axes = plt.subplots(1, 2)
         axes[0].plot(s0sMin[1:8], wKin['chiDof'], label='wKin')
         axes[0].plot(s0sMin[1:8], wCube['chiDof'], label='wCube')
         axes[0].plot(s0sMin[1:5], wQuart['chiDof'], label='wQuart')
         axes[0].set_xlabel('sparse-$s_0$: $s_{min}$')
         axes[0].set_ylabel('$\chi^2/dof$')
         axes[0].legend()

         axes[1].plot(s0sMin[1:8], wKin['chiDof'], label='wKin')
         axes[1].plot(s0sMin[1:8], wCube['chiDof'], label='wCube')
         axes[1].plot(s0sMin[1:5], wQuart['chiDof'], label='wQuart')
         axes[1].set_ylim(0, 10)
         axes[1].set_xlabel('sparse-$s_0$: $s_{min}$')
         axes[1].set_ylabel('$\chi^2/dof$')
         axes[1].legend()
```

```
Out[10]: <matplotlib.legend.Legend at 0x1a24017320>
```



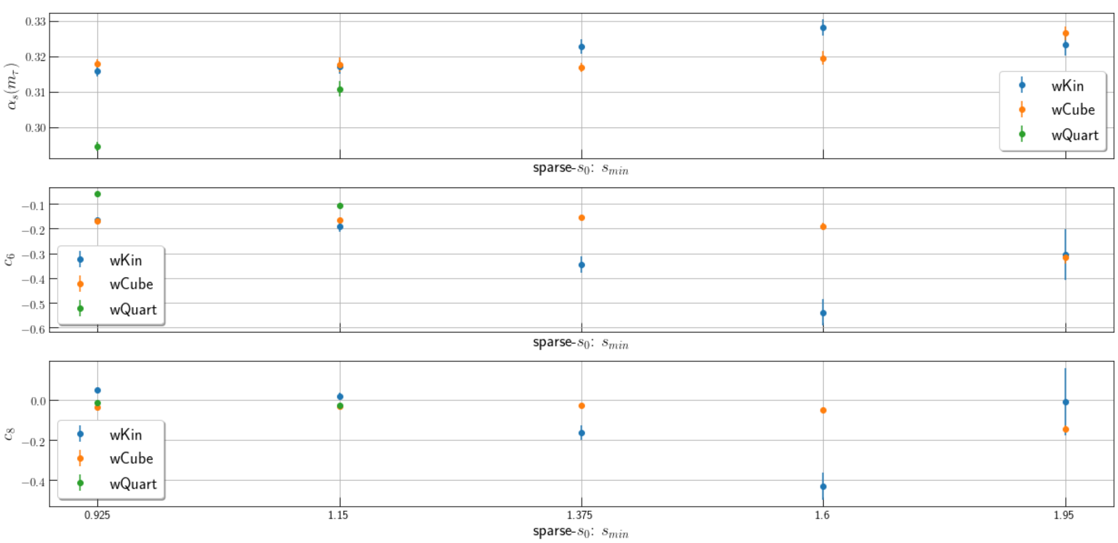
We plotted the χ^2/dof for different s_{min}. The right plot is zoomed in. We note that for low s_{min} ($s_0 < 1.15$) the χ^2/dof value is steep increasing. We also note that wQuart starts firtst to increase at $s_{min} = 1.15$ followd by wCube at $s_{min} = 0.925$ and finally wKin $s_{min} = 0.7$. Consequently in "goodness of weight" wKin is the better weight, followd by WCube and finally wQuart. The χ^2/dof values are too high for almost all fits, but get better for higher s_{min} values.

```
In [15]: fig, axes = plt.subplots(3, 1, sharex=True)
         axes[0].errorbar(s0sMin[3:8], wKin['alpha'][2:], yerr=wKin['alphaErr'][2:], label='wKi
         axes[0].errorbar(s0sMin[3:8], wCube['alpha'][2:], yerr=wCube['alphaErr'][2:], label='w
         axes[0].errorbar(s0sMin[3:5], wQuart['alpha'][2:], yerr=wQuart['alphaErr'][2:], label=
         axes[0].set_xlabel('sparse-$s_0$: $s_{min}$')
         axes[0].set_ylabel(r'$\alpha_s(m_\tau)$')
         axes[0].legend()

         axes[1].errorbar(s0sMin[3:8], wKin['c6'][2:], yerr=wKin['c6Err'][2:], label='wKin', l
         axes[1].errorbar(s0sMin[3:8], wCube['c6'][2:], yerr=wCube['c6Err'][2:], label='wCube'
         axes[1].errorbar(s0sMin[3:5], wQuart['c6'][2:], yerr=wQuart['c6Err'][2:], label='wQua
         axes[1].set_xlabel('sparse-$s_0$: $s_{min}$')
         axes[1].set_ylabel(r'$c_6$')
         axes[1].legend()

         axes[2].errorbar(s0sMin[3:8], wKin['c8'][2:], yerr=wKin['c8Err'][2:], label='wKin', l
         axes[2].errorbar(s0sMin[3:8], wCube['c8'][2:], yerr=wCube['c8Err'][2:], label='wCube'
         axes[2].errorbar(s0sMin[3:5], wQuart['c8'][2:], yerr=wQuart['c8Err'][2:], label='wQua
         axes[2].set_xlabel('sparse-$s_0$: $s_{min}$')
         axes[2].set_ylabel(r'$c_8$')
         axes[2].legend()
```

```
Out[15]: <matplotlib.legend.Legend at 0x1a25807160>
```



We plotted α_s for different sparse settings with each containing ten s_0s moments for different weights, where the smalles s_0-value is given as x-tick label. We can see that the majority of α_s

values is clustered in the interval of [0.315, 0.325]. The weights wKin and wCube show similar α_s values, whereas wQuart produces far smaller α_s values. Surprinsingly the wQuart fits only converged for lower s_{min}, which can be seen for the missing data points starting by $s_{min} = 1.375 GeV^2$.