## Runge-Kutta Methods

$$
\begin{equation*}
y^{\prime}(t)=f(t, y), \quad t \in[a, b], \quad y(a)=\alpha \tag{IVP}
\end{equation*}
$$

Fortunately, there are several ways to achieve the higher order l.t.e. of the Taylor methods without the need to evaluate $f^{\prime}, f^{\prime \prime}, \ldots$ The most popular single-step IVP solvers currently in use are the Runge-Kutta (R-K) methods.

Recall that $m=\left(y_{k+1}-y_{k}\right) / h$ is the ideal value for the quantity $\phi\left(t_{k}, y_{k}\right)$ in the single-step method $w_{k+1}=w_{k}+h \phi\left(t_{k}, w_{k}\right)$. Now view $m$ as the average value of $y^{\prime}$ over the interval $\left[t_{k}, t_{k+1}\right]$. The R-K perspective is to approximate $m$ by averaging approximate samples of $y^{\prime}$ from this interval. Euler's method is the R-K method which approximates the average value of the slope on $\left[t_{k}, t_{k+1}\right]$ by an approximation to its value at the left endpoint:

$$
m \approx y^{\prime}\left(t_{k}\right) \approx f\left(t_{k}, w_{k}\right) \equiv \phi_{\text {Euler }} .
$$

If we think the left endpoint is not as representative as the midpoint, we can use

$$
m \approx y^{\prime}\left(t_{k}+h / 2\right) \approx f\left(t_{k}+\frac{h}{2}, w_{k}+\frac{h}{2} f\left(t_{k}, w_{k}\right)\right) \equiv \phi_{\text {Midpoint }} .
$$

Maybe an average of the left and right endpoints seems better

$$
m \approx \frac{1}{2}\left(y^{\prime}\left(t_{k}\right)+y^{\prime}\left(t_{k}+h\right)\right) \approx \frac{1}{2}\left(f\left(t_{k}, w_{k}\right)+f\left(t_{k}+h, w_{k}+h f\left(t_{k}, w_{k}\right)\right)\right) \equiv \phi_{\text {ModEuler }}
$$

These last two (Midpoint and Modified Euler) methods have l.t.e. $\mathrm{O}\left(h^{2}\right)$ and require 2 $f$-evals per iteration. R - K methods all have the form:

$$
\phi_{\mathrm{RK}}=\sum_{i=1}^{m} r_{i} f\left(t_{k}+\tau_{i}, K_{i}\right),
$$

where $\tau_{i} \in[0, h]$ and $K_{i}$ is another sum of $f$-values evaluated (hopefully) near the solution graph in $\left[t_{k}, t_{k+1}\right]$.

For now we avoid the question of how to construct the weighted average of nested function evaluations that give a method with a certain l.t.e., but in order to do that one needs to determine where to sample the slope field (which $\tau_{i}$ and $K_{i}$ above), and what weights to give these values (which $r_{i}$ ).

There has been a tremendous amount of work done in this area, and we will end this too brief introduction by stating a theorem which tells us the best possible l.t.e. that can be achieved by a R-K method using n function evaluations per step.

## Theorem:

$$
\begin{array}{ccccccc}
\text { \# f-evals per step } & 2 & 3 & 4 & n=5,6,7 & n=8,9 & n=10,11 \\
\text { best possible l.t.e. } & \mathrm{O}\left(h^{2}\right) & \mathrm{O}\left(h^{3}\right) & \mathrm{O}\left(h^{4}\right) & \mathrm{O}\left(h^{n-1}\right) & \mathrm{O}\left(h^{n-2}\right) & \mathrm{O}\left(h^{n-3}\right)
\end{array}
$$

